John D. Wilson — Director of Research, Southern Alliance for Clean Energy

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EXPERIENCE

Southern Alliance for Clean Energy

Director of Research, Asheville, North Carolina and Washington, DC, 2007 – present
- Manage technical and regulatory advocacy
- Conduct supporting research and policy development across all program areas

Galveston-Houston Association for Smog Prevention

Executive Director, Houston, Texas, 2001 – 2006
- Member, Regional Air Quality Planning Committee
- Member, Transportation Policy Technical Advisory Committee
- Member, Steering Committee, TCEQ Interim Science Committee
- Awards & recognition from the City of Houston, *Houston Press*, and environmental groups

The Goodman Corporation

Senior Associate, Houston, Texas, 2000 – 2001
- Transportation and Urban Planning Consulting
- Project Manager, Houston Main Street Corridor
- Project Manager, Houston Downtown Circulation Study
- Project Manager, Austin Corridor Planning
- Project Manager, Ft. Worth Berry Street Corridor Initiative

Florida Legislature

Senior Legislative Analyst and Technology Projects Coordinator, Office of Program Policy Analysis and Government Accountability, Tallahassee, Florida, 1997- 1999
- Coordinator, Florida Government Accountability Report, 1999
- Coordinator, Project Management Software Implementation, 1999
- Creator and Editor, *Florida Monitor Weekly*, 1998 - 99
- Author or team member for reports on water supply policy, environmental permitting, community development corporations, school district financial management and other issues – most recommendations implemented by the 1998 and 1999 Florida Legislatures

Florida State University

Environmental Management Consultant, Tallahassee, Florida, 1997
- Project staff, *Florida Assessment of Coastal Trends*, 1997

Houston Advanced Research Center

Research Associate, Center for Global Studies, The Woodlands, Texas, 1992 - 96
- Coordinator, Houston Environmental Foresight, 1993 - 96
- Coordinator, Rio Grande/Rio Bravo Basin Initiative, 1992 - 94
- Secretary, Task Force on Climate Change in Texas, 1992 - 94
- Researcher, *Policy Options: Responding to Climate Change in Texas*, 1992 - 93

US Environmental Protection Agency

Student Assistant, Climate Change Division, Washington, DC, 1991 - 92
- Special Achievement Award, 1991

EDUCATION

Harvard University

Master in Public Policy, John F. Kennedy School of Government, 1992
- Concentration areas: Environment, negotiation, economic and analytic methods

Rice University

Bachelor of Arts, conferred *cum laude*, 1990
- Majors: Physics (with honors) and history

Additional Training and Experience

Spanish language; Advanced computer skills; Served and led political committees for the Sierra Club and Clean Water Action; Certified Master Wildlife Conservationist, Leon County Extension Service

PUBLICATIONS

Expert Witness Testimony

Hamilton Davis and John D. Wilson, Joint Direct Testimony on Behalf of South Carolina Coastal Conservation League and Southern Alliance for Clean Energy, *In the Matter of Joint Application of Duke Energy Carolinas, LLC and North Carolina Electric Membership Corporation for a Certificate of Environmental Compatibility and Public Convenience and Necessity for the Construction and Operation of a 750MW Combined Generating Plant Near Anderson, SC,* South Carolina Public Service Commission Docket No. 2013-392-E (December 10, 2013).

John D. Wilson, Direct Testimony on Behalf of Southern Alliance for Clean Energy, *In the Matters of Georgia Power Company's 2013 Integrated Resource Plan and Application for Decertification of Plant Branch Units 3 and 4, Plant McManus Units 1 and 2, Plant Kraft Units*

1-4, Plant Yates Units 1-05, Plant Boulevard Units 2 and 3, and Plant Bowen Unit 6, Georgia Public Service Commission Docket No. 36498 (May 10, 2013).

John D. Wilson, allowable ex parte briefing on behalf of Southern Alliance for Clean Energy, South Carolina Coastal Conservation League, and Upstate Forever, in *Progress Energy Carolinas, Incorporated's Integrated Resource Plan (IRP)*, South Carolina Public Service Commission Docket NO. 2011-8-E and in *Duke Energy Carolinas, LLC – 2011 Integrated Resource Plan*, South Carolina Public Service Commission Docket NO. 2011-10-E (December 21, 2011).

John D. Wilson, allowable ex parte briefing on behalf of Southern Alliance for Clean Energy, South Carolina Coastal Conservation League, and Upstate Forever, in *South Carolina Electric & Gas Company's Integrated Resource Plan*, South Carolina Public Service Commission Docket NO. 2011-9-E (June 1, 2011).

John D. Wilson, Direct Testimony on Behalf of Southern Alliance for Clean Energy, *In the Matters of Georgia Power Company's Application for Certification of its Demand Side Management Program*, Georgia Public Service Commission Docket No. 31082 (May 7, 2010).

John D. Wilson, Direct Testimony on Behalf of Southern Alliance for Clean Energy, *In the Matters of Georgia Power Company's Application for Approval of its 2010 Integrated Resource Plan*, Georgia Public Service Commission Docket No. 31081 (May 7, 2010).

John D. Wilson, Direct Testimony on Behalf of Environmental Defense Fund, The Sierra Club, Southern Alliance for Clean Energy, and the Southern Environmental Law Center, *In the Matter of Investigation of Integrated Resource Planning in North Carolina – 2009*, North Carolina Utilities Commission Docket No. E-100, Sub 124 (February 19, 2010).

John D. Wilson, Direct Testimony on Behalf of Environmental Defense Fund, the Natural Resources Defense Council, the South Carolina Coastal Conservation League, Southern Alliance for Clean Energy, and the Southern Environmental Law Center, *Application of Duke Energy Carolinas, LLC for Authority to Adjust and Increase Its Electric Rate and Charges,* South Carolina Public Service Commission Docket No. 2009-226-E (November 6, 2009).

John D. Wilson, Direct Testimony & Exhibits on behalf of Southern Alliance for Clean Energy and the Natural Resources Defense Council in *RE: Commission Review of Numeric Conservation Goals Florida Power & Light Company*, Florida Public Service Commission Docket No. 080407-EG, also filed in Dockets 080408-EG through 080413-EG (July 6, 2009).

John D. Wilson, Testimony on behalf of Environmental Defense Fund, Natural Resources Defense Council, Southern Alliance for Clean Energy, and Southern Environmental Law Center in *Application of Duke Energy Carolinas, Inc. for Approval of Save-a-Watt Approach, Energy Efficiency Rider and Portfolio of Energy Efficiency Programs*, North Carolina Utilities Commission Docket No. E-7, Sub 831 (June 19, 2009).

John D. Wilson, Surrebuttal Testimony on Behalf of Environmental Defense, the South Carolina Coastal Conservation League, Southern Alliance For Clean Energy and the Southern Environmental Law Center, In the Matter of *Application of Duke Energy Carolinas, LLC for Approval of Energy Efficiency Plan Including an Energy Efficiency Rider and Portfolio of Energy Efficiency Programs*, South Carolina Public Service Commission Docket No. 2007-358-E (January 28, 2008).

Comments and Presentations Related to Electric Utilities
(Lead author or significant contributor)

Southern Alliance for Clean Energy et al, *Shawnee Fossil Plant Units 1 and 4, Comments on the Draft Environmental Assessment*, submitted to Tennessee Valley Authority (December 9, 2014).

Southern Alliance for Clean Energy, Sierra Club, and South Carolina Coastal Conservation League, comments filed *In the Matter of Rulemaking Proceeding to Consider Revisions to Commission Rule R8-60 on Integrated Resource Planning*, North Carolina Utilities Commission, Docket No. E-100, Sub 111 (December 8, 2014).

South Carolina Coastal Conservation League and Southern Alliance for Clean Energy, comments filed *In the Matter of Duke Energy Progress, Inc.'s Integrated Resource Plan*, South Carolina Public Service Commission, Docket No. 2014-8-E (December 3, 2014).

Southern Alliance for Clean Energy, *Comments on the Environmental Protection Agency's Proposed Clean Power Plan,* Docket No. OAR-2013-0602 (December 1, 2014).

John D. Wilson, "TVA IRP Update," TenneSEIA Annual Meeting (November 19, 2014).

Southern Alliance for Clean Energy, *Comments on Allen Fossil Plant Emission Control Project Draft Environmental Assessment,* submitted to Tennessee Valley Authority (August 7, 2014).

Southern Alliance for Clean Energy, *TVA's On-Peak Dependable Capacity Method*, submitted to Tennessee Valley Renewable Information Exchange (June 10, 2014).

Southern Alliance for Clean Energy, *HVDC Wind Assessment*, submitted to Tennessee Valley Renewable Information Exchange (May 27, 2014).

Stephen A. Smith, letter to Tennessee Valley Renewable Information Exchange regarding in-Valley wind resource data provided by Southern Wind Energy Association (May 20, 2014).

Southern Alliance for Clean Energy, *Tennessee Valley Utility-Scale Solar Assessment*, submitted to Tennessee Valley Renewable Information Exchange (May 13, 2014).

John D. Wilson, "Rates vs. Energy Efficiency," 2013 ACEEE National Conference on Energy Efficiency as a Resource (September 2013).

Sierra Club and Southern Alliance for Clean Energy, reply comments filed in *Investigation of Integrated Resource Planning in North Carolina – 2012*, North Carolina Utilities Commission Docket No. E-100, Sub 137 (March 6, 2013).

Sierra Club and Southern Alliance for Clean Energy, comments filed in *Investigation of Integrated Resource Planning in North Carolina – 2012*, North Carolina Utilities Commission Docket No. E-100, Sub 137 (February 5, 2013).

South Carolina Coastal Conservation League and Southern Alliance for Clean Energy, comments filed in *Progress Energy Carolinas, LLC's Integrated Resource Plan*, South Carolina Public Service Commission Docket NO. 2012-8-E (January 25, 2013).

South Carolina Coastal Conservation League, Southern Alliance for Clean Energy, and Upstate Forever, comments filed in *Duke Energy Carolinas, LLC's Integrated Resource Plan*, South Carolina Public Service Commission Docket NO. 2012-10-E (December 6, 2012).

Southern Alliance for Clean Energy, comments filed in *Investigation of Integrated Resource Planning in North Carolina – 2010-2011*, North Carolina Utilities Commission Docket No. E-100, Sub 128 (January 13, 2012).

Southern Alliance for Clean Energy, and South Carolina Coastal Conservation League, comments filed in *Progress Energy Carolinas, Incorporated's Integrated Resource Plan (IRP)*, South Carolina Public Service Commission Docket NO. 2011-8-E (October 31, 2011).

Southern Alliance for Clean Energy, South Carolina Coastal Conservation League, and Upstate Forever, comments filed in *Duke Energy Carolinas, LLC's Integrated Resource Plan*, South Carolina Public Service Commission Docket NO. 2011-10-E (October 31, 2011).

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Southern Alliance for Clean Energy, South Carolina Coastal Conservation League, and Upstate Forever, comments filed in *South Carolina Electric & Gas Company's Integrated Resource Plan*, South Carolina Public Service Commission Docket NO. 2011-9-E (April 15, 2011).

Southern Alliance for Clean Energy, comments filed in *Investigation of Integrated Resource Planning in North Carolina – 2010*, North Carolina Utilities Commission Docket No. E-100, Sub 128 (February 10, 2011).

John D. Wilson, "Energy Efficiency Delivers Growth and Savings for Florida," testimony before Energy & Utilities Subcommittee, Florida House of Representatives (February 2011).

Southern Alliance for Clean Energy, comments filed in *RE: Petition for Approval of Demand-Side Management Plan of Progress Energy Florida*, Florida Public Service Commission Docket No. 100160-EG (June 3, 2011).

Southern Alliance for Clean Energy, comments filed in *RE: Petition for Approval of Demand-Side Management Plan of Progress Energy Florida*, Florida Public Service Commission Docket No. 100160-EG, also filed in Docket No. 100155-EG (April 25, 2011).

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No. 100154-EG, also filed in Dockets 100155, 59, and 60-EG (December 22, 2010).

Environmental Defense Fund, Southern Alliance for Clean Energy, and Southern Environmental Law Center, reply comments in *Rulemaking Proceeding to Implement Session Law 2007-397*, North Carolina Utilities Commission Docket No. E-100, Sub 113 (November 19, 2010).

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Environmental Defense Fund, Southern Alliance for Clean Energy, and Southern Environmental Law Center, comments in *Rulemaking Proceeding to Implement Session Law 2007-397*, North Carolina Utilities Commission Docket No. E-100, Sub 113 (October 15, 2010).

Environmental Defense Fund, Southern Alliance for Clean Energy, and Southern Environmental Law Center, comments in *Rulemaking Proceeding to Implement Session Law 2007-397*, North Carolina Utilities Commission Docket No. E-100, Sub 113 (October 4, 2010).

South Carolina Coastal Conservation League and Southern Alliance for Clean Energy, comments filed *In the Matter of Duke Energy Carolinas, LLC's Integrated Resource Plan*, South Carolina Public Service Commission, Docket No. 2014-10-E (November 3, 2014).

Southern Alliance for Clean Energy and Environmental Defense Fund, statement of position letter in *Application for Residential Retrofit* and *Home Energy Comparison Report Pilot Programs*, North Carolina Utilities Commission Dockets Nos. E-7 Sub 952 and Sub 954 (September 17, 2010).

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John D. Wilson, "Bringing Energy Efficiency to Southerners," Environmental and Energy Study Institute panel on "Energy Efficiency in the South" (April 10, 2010).

John D. Wilson, "The Changing Face of Energy Supply in Florida (and the Southeast)," 37th Annual PURC Conference (February 2010).

John D. Wilson, "Florida Energy Policy Discussion," testimony before Energy & Utilities Policy Committee, Florida House of Representatives (January 2010).

John D. Wilson, "Building the Energy Efficiency Resource for the TVA Region," presentation on behalf of Southern Alliance for Clean Energy to the Tennessee Valley Authority Integrated Resource Planning Stakeholder Review Group (December 10, 2009).

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Southern Alliance for Clean Energy, Comments in *RE: Establishment of Rule on Renewable Portfolio Standard*, Florida Public Service Commission Docket No. 080503-EI (December 8, 2008).

Southern Alliance for Clean Energy, Comments in *RE: Establishment of Rule on Renewable Portfolio Standard*, Florida Public Service Commission Docket No. 080503-EI (September 5, 2008).

Southern Alliance for Clean Energy, *Comments on July 11, 2008 RPS Workshop*, Florida

Public Service Commission undocketed workshop (July 2008).

Environmental Defense Fund, Natural Resources Defense Council, Southern Alliance for Clean Energy, and Southern Environmental Law Center, further comments in *Investigation of Rate Structures, Policies and Measures that Promote a Mix of Generation and Demand Reduction for Electric Power Suppliers in North Carolina*, North Carolina Utilities Commission Docket No. E-100, Sub 116 (June 23, 2008).

Southern Alliance for Clean Energy, comments on *Energy Efficiency and Demand Response Plan*, submitted to Tennessee Valley Authority (May 6, 2008).

Southern Alliance for Clean Energy, comments on *Renewable Energy and Clean Energy Assessment*, submitted to Tennessee Valley Authority (May 6, 2008).

John D. Wilson, "Utility-Scale Renewable Energy," presentation on behalf of Southern Alliance for Clean Energy to the Board of the Tennessee Valley Authority (March 5, 2008).

John D. Wilson, "Energy Efficiency: Regulating Cost-Effectiveness," Florida Public Service Commission undocketed workshop (April 25, 2008).

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Southern Alliance for Clean Energy, *Renewable Energy Standard Offer: A Tennessee Valley Authority Case Study* (November 2012).

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John D. Wilson, Tom Franks and J. Richard Hornby, "Seeking Consistency in Performance Incentives for Utility Energy Efficiency Programs," *2010 American Council for an Energy-Efficient Economy Summer Study on Energy Efficiency in Buildings* (August 2010).

John D. Wilson, "Energy Efficiency Program Impacts and Policies in the Southeast," Southern Alliance for Clean Energy (May 2009).

Dennis Creech, Eliot Metzger, Samantha Putt Del Pino, John D. Wilson, *Local Clean Power*, World Resources Institute Issue Briefs (April 2009).

Dennis Creech, Eliot Metzger, Samantha Putt Del Pino, John D. Wilson, *Green in the Grid: Renewable Electricity Opportunities in the Southeast United States*, World Resources Institute Issue Briefs (April 2009).

Southern Alliance for Clean Energy, *Yes We Can: Southern Solutions for a National Renewable Energy Standard* (February 2009).

Southern Alliance for Clean Energy, *Cornerstones: Building a Secure Foundation for North*

Carolina's Energy Future (May 2008).

Southern Alliance for Clean Energy, *Bringing Clean Energy to the Southeastern United States: Achieving the Federal Renewable Energy Standard* (February 2008).

Galveston Houston Association for Smog Prevention, *Whiners Matter! Citizen Complaints Lead to Improved Regional Air Quality Control* (June 2006).

Galveston Houston Association for Smog Prevention, *Exceeding the Limit: Industry Violations of New Rule Almost Slid Under State's Radar* (January 2006).

Galveston Houston Association for Smog Prevention, *Mercury in Galveston and Houston Fish: Contamination by Neurotoxin Places Children at Risk* (October 2004).

Environmental Integrity Project and Galveston Houston Association for Smog Prevention, *Who's Counting: The Systematic Underreporting of Toxic Air Emissions* (June 2004).

Galveston Houston Association for Smog Prevention, *Reducing Air Pollution From Houston-Area School Buses* (March 2004).

Galveston Houston Association for Smog Prevention, *Smoke in the Water: Air Pollution Hidden in the Water Vapor from Cooling Towers – Agencies Fail to Enforce Against Polluters* (February 2004).

Office of Program Policy Analysis and Government Accountability, *Florida Water Policy: Discouraging Competing Applications for Water Permits; Encouraging Cost-Effective Water Development,* Report No. 99-06 (August 1999).

John D. Wilson, Janet E. Kohlhase, and Sabrina Strawn, "Quality of Life and Comparative Risk in Houston," *Urban Ecosystems*, Vol. 3, Issue 2 (July 1999).

Office of Program Policy Analysis and Government Accountability, *Review of the Expedited Permitting Process Coordinated by the Governor's Office of Tourism, Trade, and Economic Development,* Report No. 98-17 (October 1998).

Office of Program Policy Analysis and Government Accountability, *Review of the Community Development Corporation Support and Assistance Program*, Report No. 97-45 (February 1998).

Office of Program Policy Analysis and Government Accountability, *Best Financial Management Practices for Florida School Districts*, Report No. 97-08 (October 1997).

Florida Coastal Management Program, *Florida Assessment of Coastal Trends* (June 1997).

Houston Environmental Foresight Committee, *Seeking Environmental Improvement*, Houston Advanced Research Center (January 1996).

Houston Environmental Foresight Science Panel, *Houston Environment 1995*, Houston Advanced Research Center (1996).

Judith Clarkson, John D. Wilson and Wolfgang Roeseler, "Urban Areas," in Gerald R. North, Jurgen Schmandt and Judith Clarson, *The Impact of Global Warming on Texas: A Report of the Task Force on Climate Change in Texas* (1995).

Houston Advanced Research Center, *Policy Options: Responding to Climate Change in Texas*, US EPA and Texas Water Commission (October 1993).

Increased Levels of Renewable Energy Will Be Compatible with Reliable Electric Service in the Southeast

Summary

Utilities in the Southeast are beginning to consider deployment of variable renewable energy resources on their systems, with some proposals suggesting that 10-20% of annual electricity demand might be sourced from wind and solar in the next decade. Elsewhere in the country, technical experts have concluded that variable renewable energy resources can meet at least 50% of electric system demand using currently available technology and system management capabilities,, provided that utilities make "investment in additional distribution and transmission system infrastructure as well as changes in electric system operations, markets, and planning to achieve reliability."[1] Across much of the United States, these questions are systematically addressed through the planning processes of regional transmission operators (RTOs), independent system operators (ISOs) and super-regional planning organizations such as the Western Electricity Coordinating Council.

However, in the Southeast, several large vertically-integrated utilities conduct their own resource adequacy, reliability and operational planning with minimal market exposure. Due to historically limited solar and wind development, vertically-integrated utilities in the Southeast have not provided analyses of renewable energy that are as comprehensive or similarly robust as those in RTO or ISO regions. While few of their planning studies have thoroughly examined renewable energy resources, these studies do often raise questions regarding renewable resource adequacy, reliability and flexibility.

This study summarizes the information available from these utilities, and answers the following key questions with analysis that could be used in a variety of energy planning activities.

1. **How much conventional capacity can be replaced by:**

   - **Solar photovoltaic (PV) power resources?** For every 100 megawatts (MW) of solar power resources, about 50-70 MW of conventional generation capacity can be avoided. The exact value depends on the location and technology used.

   - **Southeastern wind power resources?** For every 100 MW of wind resources generated in the Southeast, the limited available data suggest 10-15 MW of conventional generation capacity can be avoided. Both technology change and the lack of data suggest that these estimates are subject to revision.

   - **Wind power imported via HVDC transmission?** For every 100 MW of wind resources imported into the Southeast via HVDC transmission, about 45-60 MW of conventional generation capacity can be avoided. The exact value depends on the wind characteristics, the business model for the

[1] Linvill, C., Migden-Ostrander, J. and Hogan, M., *Clean Energy Keeps the Lights On*, Regulatory Assistance Project (June 2014).

transmission provider, and the amount of "wheeling" from one utility system to another that is needed.

2. **Will these *capacity values* change if renewable energy penetration levels increase?** Yes, if the Southeast deploys a mix of solar and wind resources to meet 10-20% of annual electricity demand, these values will change. For solar, the values would drop to 25-40 MW; for regional wind, the values would increase slightly; for HVDC wind imports, the values would drop to 20-40 MW per 100 MW of conventional generation.

3. **Will renewable energy cause utility system *reliability* to decrease at:**

   - **Current or projected near-term penetration levels?** No, while renewable energy resources are variable, they perform very well during high demand periods when utility systems need to use most of their generation resources. On average, regional solar and imported wind resources should generate at 50-60% dependable capacity factors during these hours in the Southeast. At current and near-term levels of renewable energy use, long-term modeling analysis indicates no increased reliability risks at the system level – even during hours in which renewable energy production might be low.

   - **Significantly higher levels of renewable energy development?** No, even if renewable energy is increased to meet 10-20% of annual electricity demand, reliability should be relatively unaffected on balance. At these higher levels of renewable energy use, there would be a balance of increased and decreased risks that utilities would need to study and monitor. Hours with increased reliability risks would occur very infrequently, roughly only one hour per year on average. However, that same level of renewable energy generation would actually increase the number of hours in which reliability is ensured by about 80 hours per year.

4. **Could solar power cause some utility systems to effectively shift from a summer to winter peak, thus negating its benefits during a "polar vortex" type event?** Winter peaks in the Southeast are occasionally nearly as high as summer peaks. Nonetheless, even with several gigawatts (GW) of solar energy added to existing utility systems, winter peaks did not become the most challenging reliability condition in any of the utility systems we studied. It is important to study this potential effect in the context of other system resources. Because conventional generation operates more efficiently during winter peaking episodes, a system planned for summer peak will have more conventional capacity available in the winter to compensate. Furthermore, wind power produces very well during winter peaking episodes. In general, an optimized approach to resource, operation and reliability studies should be sufficient to plan for a "polar vortex" type event.

5. **Will conventional generation plants have to ramp up and down rapidly to balance variable renewable generation?** Utility operators will not need to increase the ramping of conventional generation under current and projected near-term renewable energy penetration levels. Up to around 10% of energy supply, utility systems may actually be easier to operate, since solar energy in the Southeast is closely aligned with system peaks. While the transition point depends on the utility system and the resources applied, even at 10-20% of annual electricity demand, the California "duck curve" problem of high ramp rates for conventional generation is unlikely to appear in the Southeast.

These questions have been answered by matching industry-standard data about potential wind and solar generation to the historical generation data supplied by Duke Energy (in the Carolinas), Southern Company (including Alabama, Florida, Georgia and Mississippi subsidiaries), and the Tennessee Valley Authority (serving portions of seven Southeastern states). The methods applied in this analysis utilize industry-standard techniques, enhanced to more carefully examine reliability and capacity value concerns regarding renewable energy development in the Southeast.

1. Dependable (on-peak) Capacity Values of Renewable Energy Resources in the Southeast[2]

In determining whether a utility has adequate resources to meet its forecast system requirements, Southeastern utilities utilize a dependable capacity factor (DCF) for renewable energy resources. (Elsewhere these may be referred to as an on-peak capacity value, a generation capacity credit, or by some other nomenclature.) The DCF may be thought of as a "derating factor" which takes into account not only the output capabilities of a renewable energy resource, but also the usefulness of the resource output in meeting overall electric utility system reliability standards.[3] Under current and projected near-term penetration levels, this analysis demonstrated that a mix of renewable energy resources can be deployed in the Southeast using a DCF of approximately 50%. This means that utility operators would be able to assume that renewable energy resources reliably produce about half of the rated nameplate capacity during hours of peak electric demand.

Each electric resource comes with its own operational constraints and capabilities, which are routinely quantified by utilities. Modern natural gas plants offer rapid start and turndown capabilities. Nuclear power output can typically be varied within a narrow band, but operational and financial considerations make it impractical to vary much with load on an hourly or even daily basis. Large steam plants (fossil and nuclear) require hours to start up, more hours to reach full outputs, and shut downs cover even more hours. Outputs from thermal generation resources are often higher in the winter, reflecting greater operating efficiencies due to cooler water and air temperatures. Each generating unit demonstrates an evolving forced outage rate reflecting its inherent reliability and the need for system redundancy. These and many other factors are properly quantified by utilities within the context of reserve margin and resource planning studies.

In contrast to an evenhanded, data-driven approach, Southeastern utilities have sometimes emphasized the "operational limitations" of renewable energy in a less rigorous or systematic manner. For example, Duke Energy describes solar energy as a resource that:

> …cannot be dispatched to meet changing demand from customers all hours of the day and night, through all types of weather … by way of comparison: Solar energy's equivalent full output is available approximately 20% of the time. Nuclear energy's equivalent full output is available greater than 90% of the time. Natural gas combined cycle's energy is available greater than 90% of the time. As a result, it can take 4 to 5 MW of installed solar generation to produce

[2] See Attachment A for more detail on this topic.

[3] Styled after definition of ELCC, as described by California Public Utilities Commission, Energy Division, *Effective Load Carrying Capacity and Qualifying Capacity Calculation Methodology for Wind and Solar Resources*, Staff Proposal, Resource Adequacy Proceeding R.11-10-023 (January 16, 2014), p. 1.

> the same amount of energy that is available from a single MW of natural gas or nuclear generation.[4]

Elsewhere in the same document, Duke Energy attributes a 45% DCF to solar energy, but its operational summary makes clear that the corporate view of solar is that of an impaired, barely relevant resource. While the *energy* produced by solar and wind resources is variable and not represented by its peak output, modern forecasting techniques and the geographic dispersal of these resources provide utilities with the opportunity to plan for and control gradual or even sudden changes in solar and wind power production.[5]

Southeastern utilities appear to have adopted capacity factor-based approximation methods for measuring DCFs.[6] A relatively simple approach that provides "basic insight into the coincidence of [renewable] generation and load," it is not frequently used in major studies of renewable generation due to the "widespread acceptance and use of more sophisticated methods."[7] The preferred metric for measuring the DCF is the effective load carrying capability (ELCC) method. However, the ELCC method requires, among other data, a "complete inventory of conventional generation units' capacity, forced outage rates and maintenance schedules."[8] With Southeastern utilities in significant flux, considering a high number of ongoing plant retirements and new generation in process, it is impractical for a non-utility planning study to obtain a useful forecast with a "complete inventory" of these data.

In a study that reviewed the methods used by Southeastern utilities for measuring DCFs, it was noted that they are less useful and potentially inaccurate relative to the ELCC because they do not "capture the short term or annual variability" of variable renewable energy resources, or their correlation with demand throughout the year.[9] In order to address this shortcoming without engaging in an impractical forecasting effort, a new variant of the capacity factor-based approximation method, the System Peak Hours (SPH) method, is utilized in this analysis and described in greater detail in Appendix A. The SPH method is effective at capturing both the short-term (hourly) correlation with demand, as well as the annual variability of renewable energy resources. The SPH method improves on other capacity factor-based approximation methods by using a matched, multi-year set of renewable energy generation and utility system demand data.

For example, TVA's current method for establishing the DCF of solar power resources is the average summer capacity factor during the 5 – 6 pm CDT (also referred to as CPT or central planning time) hour.[10] An evaluation of TVA's system load data shows that this hour has been one of the top 20 system

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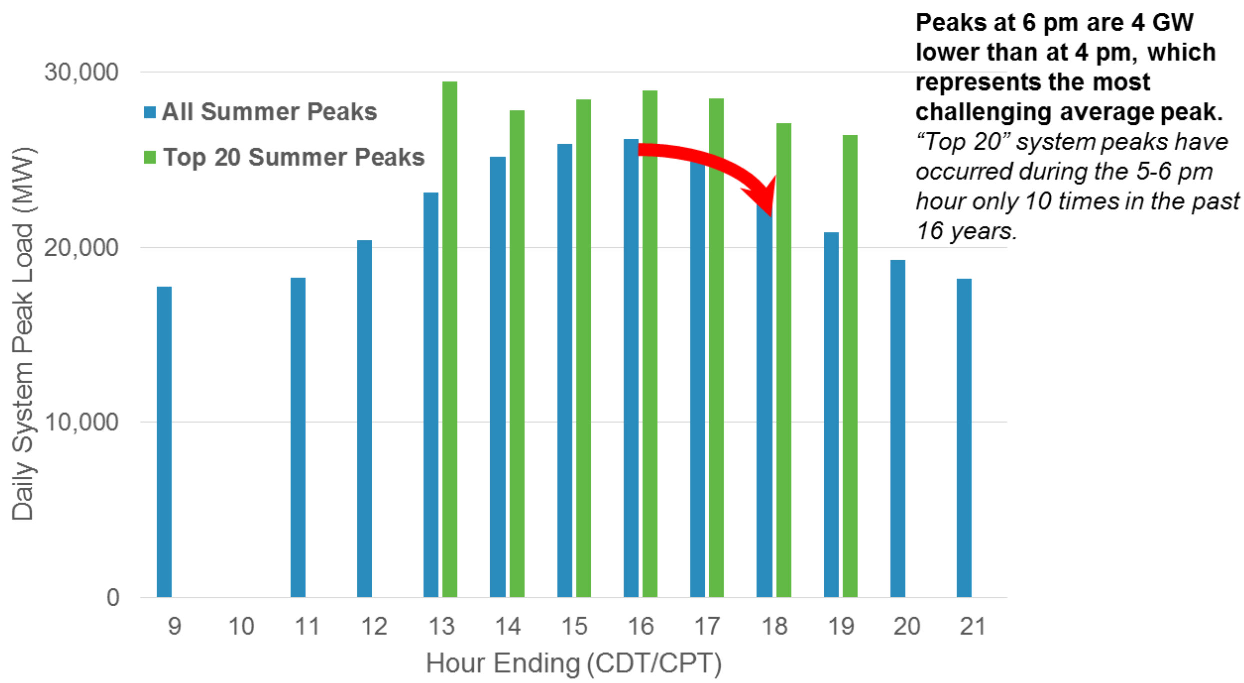
[4] Duke Energy Carolinas, *Integrated Resource Plan (Annual Report)* (September 1, 2014), p. 6.
[5] Ela, E. et al., *Active Power Controls from Wind Power: Bridging the Gaps*, National Renewable Energy Laboratory, University of Colorado, and Electric Power Research Institute, NREL Technical Report NREL/TP-5D00-60574 (January 2014).
[6] Not all Southeastern utilities that measure DCFs have publicly described their methods.
[7] Denholm, P. et al., *Methods for Analyzing the Benefits and Costs of Distributed Photovoltaic Generation to the U.S. Electric Utility System*, National Renewable Energy Laboratory, NREL Technical Report NREL/TP-6A20-62447 (September 2014).
[8] Keane, A. et al., "Capacity Value of Wind Power," *IEEE Transactions on Power Systems* (v. 26, no. 2), Task Force on the Capacity Value of Wind Power, IEEE Power and Energy Society (September 2010), p. 3.
[9] Keane (2010), p. 4.
[10] Tennessee Valley Authority, "2015 Integrated Resource Plan: IRPWG Meeting Session 7 – Day 2," (May 30, 2014) Slide 27.

peaks only 10 times over a 16-year period (about 3% of such peaks). Furthermore, as illustrated in Figure 1, TVA system peaks at 6 pm are 4 GW lower than at 4 pm. In other words, daily peaks occurring at 4 pm are usually more than 13% higher than daily peaks occurring at 6 pm. Thus, the hour that TVA has chosen to use to evaluate solar system performance is neither representative of typical system peaks nor is it representative of periods in which system capacity needs are particularly stretched. The SPH method is designed to focus on hours that are representative of periods in which system capacity needs are stretched, and to exclude hours in which system capacity needs are easily met by the utility's power resources.

Figure 1: TVA System Summer Peaks (1998-2013)



Because the SPH method and the measurement methods used by Southeastern utilities all use capacity factor averaging during peak periods, it is not surprising that a comparison of those measurements shows that they are sometimes in rough agreement. TVA's method for wind resources is different from that used for solar. Briefly summarized, TVA averages the capacity factor for the peak hour on each of the 20 peak days during the summer season.[11] Although not as well documented, Duke Energy (in the Carolinas) and Southern Company (whose values are not publicly disclosed) appear to use a peak-period capacity factor averaging method that utilizes a block of summer hours.[12]

Based on the analysis conducted for this report using the SPH method, as illustrated in Figure 2, the following results were demonstrated in the Southeast:

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[11] Tennessee Valley Authority, "2015 Integrated Resource Plan: IRPWG Meeting Session 7 – Day 2," (May 30, 2014) Slide 25.

[12] Duke Energy Carolinas, *Integrated Resource Plan* (September 2014); and Duke Energy Progress, *Integrated Resource Plan* (September 2014). Georgia Power Company, *Advanced Solar Initiative and ASI-Prime Request for Proposals for Solar Photovoltaic Generation,* Attachment G (March 10, 2014).

- For every 100 MW of solar power resources, about 50-70 MW of conventional generation capacity can be avoided. The exact value depends on the location and technology used. TVA's values are in close agreement with these, Duke's 45 MW value appears somewhat low, and Southern Company does not disclose its DCF value.
- For every 100 MW of wind resources generated in the Southeast, the limited available data suggest 10-15 MW of conventional generation capacity can be avoided. Both technology change and the lack of data suggest that these estimates are subject to revision. These values are consistent with (even a bit lower than) the values used by TVA and Duke (again, Southern Company does not disclose its DCF value).
- For every 100 MW of wind resources imported into the Southeast via HVDC transmission,[13] about 45-60 MW of conventional generation capacity can be avoided. The exact value depends on the wind characteristics, the business model for the transmission provider, and the amount of "wheeling" from one utility system to another that is needed. Even though TVA is actively considering the import of these resources, TVA is currently utilizing a much lower value derived from market experience with wind resources from other regions.

Considering projected or likely near-term renewable energy development pathways, a mix of renewable energy in any Southeastern utility territory is likely to have a dependable capacity rating of roughly 50%.

[13] Imports of wind energy via regional AC transmission grids were not studied.

Figure 2: Summer Dependable Capacity Factors Calculated Using System Peak Hours Method, Assuming No Substantial Prior Renewable Energy Development

2. Impact of Renewable Energy Development on Dependable Capacity Factors[14]

If the Southeast deploys a mix of solar and wind resources to meet 10-20% of annual electricity demand, the DCFs will decrease. For solar, the values would drop to 25-40 MW; for regional wind, the values would increase slightly; for HVDC wind imports, the values would drop to 20-40 MW per 100 MW of conventional generation.

Few utilities in the Southeast currently account for the general decline in the DCFs of renewable energy resources as grid penetration increases. The DCF decreases as grid penetration increases because the number of hours in which the utility faces significant capacity shortfalls decreases during times when renewable energy is generating. (This shift is also examined in Section 4.) This may not be an important oversight if low grid penetration is assumed, but planning for scenarios with 10-20% of energy supplied by renewable energy generation clearly requires such consideration.

For example, DCFs for utility-scale solar power resources in the three utility service areas today are at very similar levels for both fixed mount systems (49-54% DCFs) and single-axis tracking systems (60-63%). However, as illustrated in Figure 3, at higher levels of deployment, the DCFs diverge somewhat. For Duke Energy, which has the least wind power included in its scenario, the DCF values do not decrease as much as for the other two utilities. (The scenarios, as described in Appendix A, included over 4,000 MW of solar plus varying amounts of wind, but dependable capacity values were only estimated at 2,650 – 3,800 MW, depending on the utility scenario.)

Although there are some differences driven by the distinct characteristics of each utility scenario, the overall finding for solar is that there is a consistent alignment of solar energy production relative to the system load shapes across the Southeast, and the impact of solar development on DCF values decreases in a consistent manner.[15] Another interesting observation is that higher capacity values are generally obtained towards the western portion of the region. This can be seen by noting the slight improvement for solar in Alabama, Florida or Mississippi relative to Georgia, but is also observed within the TVA dataset.

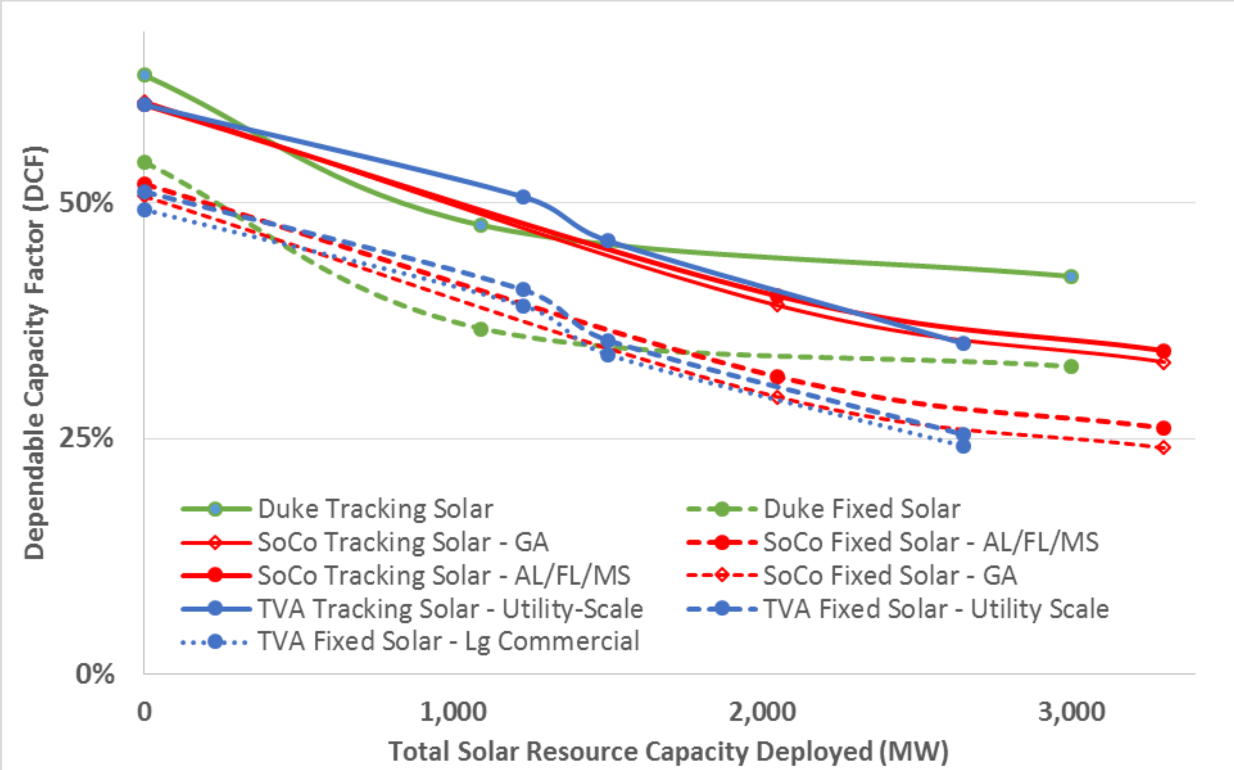
Other sources of potential capacity value sometimes overlooked by utilities are the value of regional coordination, and synergies among different resources. Both of these features are considered in this analysis. Regional coordination benefits are demonstrated by higher capacity values obtained by assuming that much of the solar energy development would occur in utility areas with higher DCFs. As described in Appendix A, utilizing an average of several sites demonstrated better performance than just using any single site.

Furthermore, as illustrated further in Appendix A, the application of wind and solar resource development together in scenarios resulted in a better understanding of how DCFs would likely evolve under foreseeable development scenarios. For example, even though DCFs for wind alone would decrease with its development, in combination with solar development, the DCFs instead increase.

[14] See Appendix A for greater detail on this topic.

[15] Solar DCFs do vary somewhat as wind resources are deployed. The sharp, but small, drop in TVA's DCF values between Tranches 2 and 3 appears to be caused by wind resource deployment.

Figure 3: Impact of Scale of Development on Solar Power Dependable Capacity Factors

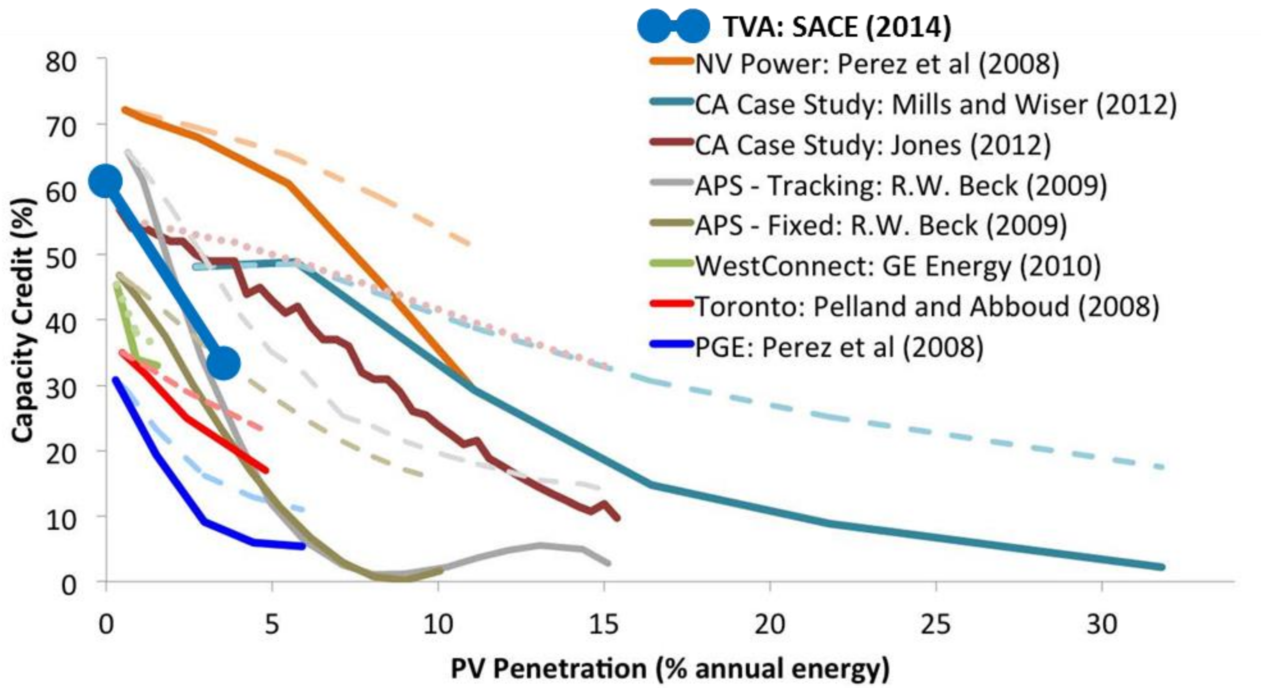


The trends observed in Figure 3 are consistent with findings for other utilities across the country. For example, TVA's average solar DCF (fixed and solar) is plotted against similar values from other utilities in Figure 4.[16] (DCFs are referred to as "capacity credit" in the figure, and the 3,950 MW of solar energy studied over the 1998-2012 study period represents about 4.4% of TVA system demand at the higher end of the TVA trend in the figure.) These findings also suggest that the Southeast has relatively high DCF values for solar.[17]

[16] Mills, A. and R. Wiser, *An Evaluation of Solar Valuation Methods Used in Utility Planning and Procurement Processes*, Lawrence Berkeley National Laboratory, LBNL-5933E (December 2012).

[17] This advantage was first observed by Richard Perez in the early 1990s. Perez, R., S. Letendre and C. Herig, *PV and Grid Reliability: Availability of PV Power During Capacity Shortfalls*, Proc. ASES Annual Meeting (2001).

Figure 4: TVA Solar Dependable Capacity Factor Contrasted with Other Utilities Summarized by LBNL



3. *Impact of Renewable Energy Development on Utility System Reliability*[18]

While renewable energy resources are variable, they perform very well during high demand periods when utility systems need to use most of their generation resources. On average, regional solar and imported wind resources should generate at 50-60% capacity factors during these hours. However, the level of renewable energy generation in the Southeast today and planned for the near-term is not large enough to increase system reliability risks – even during hours in which renewable energy production might be low.

Furthermore, even if renewable energy is increased to meet 15% or more of energy requirements, reliability should be relatively unaffected. At these higher levels of renewable energy use, there would be a balance of increased and decreased risks that utilities would need to monitor and manage.

To place the balance of risks in context, it is worth noting that during the vast majority of hours of the year, system demand for a utility is well below available resources. For example, the three utilities studied here would typically have a 25% (or greater) capacity surplus for 98% of the year. During those remaining hours, the utility would manage a very small risk that available generation would not be sufficient to meet demand.

Thus, utility system reliability would change in both directions, there would be reliability risks and benefits associated with renewable energy development. Hours with increased reliability risks would occur very infrequently, roughly one hour per year on average (an adverse effect). However, that same

[18] See Appendix B for greater detail on this topic.

level of renewable energy generation would also improve reliability by reducing the number of "risky" hours by 20-40% (a beneficial effect).

With the data available to this analysis, it is not possible to quantitatively demonstrate whether the benefits outweigh the adverse effect.[19] Nonetheless, it is possible to arrive at some quantitative observations of these competing effects by identifying the results of two key metrics:

- **Higher risk hours**: The number of hours in which renewable energy, in a well-planned system, results in lower hourly capacity reserves.[20]
- **Reliability ensured hours**: The reduction in the number of hours with a significant probability of reliability incidents, defined as capacity reserves of less than 125% of hourly demand.

As illustrated in Figure 5, the ratio of higher risk hours to reliability ensured hours is 1:76 or less, with a clearly positive impact appearing to occur on the Duke Energy system on which no higher risk hours result, even though the scenario studied was heavily weighted towards solar power.

Figure 5: Impact of Renewable Energy Development Scenarios on Reliability

	Higher Risk Hours	Reliability Ensured Hours	Ratio
Duke Energy (North and South Carolina)	0.0 % (0)	0.734 % (558)	0:100
Southern Company	0.007 % (6)	0.549 % (481)	1:80
Tennessee Valley Authority	0.008 % (11)	0.639 % (840)	1:76

Even if the ratio of higher risk hours to reliability ensured hours is very low, it would be reasonable to be concerned that there could be specific hours in which a system that depends on high levels of renewable energy might be at greater reliability risk due to highly unusual circumstances. Utility executives have raised just this concern, citing reliability challenges that occurred during the recent "polar vortex" and speculating about the difficulty of meeting those challenges with high levels of solar penetration.[21] This anecdotal concern is discussed in the following section.

The more general concern that might be raised is that these results just seem implausible. Some readers may be dubious that replacing 3-4 GW of conventional generation with 8 GW of renewable energy (e.g., in the case of TVA) could result in little or no decrease in reliability. This concern can be addressed in two ways.

First, the use of a forecast scenario of renewable energy deployment guides utilities towards an appropriate amount of dispatchable capacity that may be replaced with variable resources. So the 8 GW of nameplate renewable energy capacity studied for the TVA system offsets "only" 4 GW of dispatchable generation capacity. It should be noted that this substantial change would also result in the utility

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[19] The underlying methods of a target reserve margin study involve stochastic evaluation of probabilities. For example, in a random draw of circumstances, the utility may not experience a reliability event during an hour with an effective reserve margin of 10%, but might experience a reliability event during an hour with an effective reserve margin of 20%.

[20] In other words, the number of hours in which the utility might consider taking additional measures to ensure no added risk of a reliability incident.

[21] Mazzocchi, Lee, "The Challenge of Making the Electric Grid Better," EPRI Smart Distribution and Power Quality Conference (July 2014).

changing its dispatchable generation fleet by adjusting the optimal mix of new capacity (e.g., gas peaker versus combined-cycle units). Those changes in the expansion plan would be developed in a resource planning study.

Second, the use of a multi-year dataset ensures that the resulting planning standards incorporate many different actual challenges to reliability. Some hours are more reliable, some hours are less reliable. Implausible examples can be constructed to make any resource plan look risky. Isolating the analysis to a particular "strawman" hour would ignore the improvements in many other hours.

For example, the probability of solar, in-region wind and imported wind power dropping from 8 GW to 0 GW in a single hour is no more likely nor relevant to the planning of the three utility systems analyzed here than the loss of 8 GW of nuclear capacity in a single hour. Any "perfect storm" scenarios a utility might wish to address could be addressed with specific mitigation measures (e.g., modifying a thermal generation unit to be more reliable at cold temperatures). By considering aggressive, but realistic scenarios of renewable energy development in the context of actual system conditions for over a decade, the likelihood that an extreme event has been overlooked has been minimized.

4. Role of Solar Power on Utility Systems During Winter Peak or "Polar Vortex" Type Events

As solar power is developed to scale, the net system peak may shift from primarily summer afternoon hours to include more summer evening and winter morning hours. Since the output of solar systems is relatively small (or zero) during those hours, the contribution of solar power to meeting system peak needs would be diminished. As discussed above, with increasing amounts of solar power deployed on utility systems, the DCFs for solar systems declines. However, some may be concerned that depending on capacity from solar systems might put the utility at greater risk during an extreme winter peak event (e.g., "polar vortex").

In fact, none of the utility systems we studied demonstrate such a problem. The data sets used for this study include three utilities studied over more than a full decade of historical hourly load data, totaling literally hundreds of thousands of hours. As illustrated above in Figure 5, the total number of hours in which the effective reserve margin for these three utilities was worse with renewables than without is only 17 hours, or less than 0.01% of the hours in the analysis period.

One reason that winter peaks are not a problem is that the winter peaking hours in the Southeast tend to be significantly lower than the annual forecast peak. For Southern Company, in fact, the maximum winter load hour within the ten year dataset was only 96% of the forecast annual peak. For Duke Energy and TVA, there were a few winter load hours that exceeded 100% of the forecast annual peak, but the vast majority of winter load hours were 95% of the forecast annual peak or less. In short, Southeastern utility systems almost always have an adequate buffer between winter peaks and the forecast annual peak.

This buffer is reinforced by the more efficient operation of conventional generation during the winter. system planned for summer peak will have more conventional capacity available in the winter to compensate. For thermal generation resources, such as natural gas units or nuclear power, the winter capacity rating is typically somewhat higher, resulting in a summer "shortfall." For renewables, the DCF of solar energy is higher in the summer than in the winter, indicating a summer "shortfall." Thus, the potential for capacity needs to be determined in the winter rather than summer would occur when the winter "shortfall" of renewable energy resources is greater than the summer "shortfall" of thermal generation resources. As illustrated in Figure 6, for two of the three utilities considered it appears unlikely that the levels of renewable energy studied would in and of themselves cause the peak to shift from summer to winter.

Figure 6: Impact of Substantial Renewable Energy Development Scenarios on Seasonal Peak

Dependable Capacity (MW)	**Thermal Generation**			**Renewable Generation Scenario**		
	Summer	Winter	Summer "Shortfall"	Summer	Winter	Winter "Shortfall"
Duke Energy (Carolinas)[22]	35,467	37,302	**1,835**	2,246	619	**1,627**
Southern Company[23]	41,522	43,095	**1,573**	3,099	2,312	**787**
Tennessee Valley Authority[24]	40,040	41,157	**1,117**	3,141	1,890	**1,251**

Even though the Duke Energy scenario does not suggest any reliability issues (as summarized in the discussion related to Figure 5), it should be discussed further here because it is an almost all-solar scenario. Due to the lack of hourly generation data stretching back for a decade or more for wind resources available in or near Duke Energy's territory in the Carolinas, the maximum renewable scenario for Duke Energy in this study only includes 500 MW of wind resources, delivered via HVDC transmission and wheeled across the TVA and Southern Company systems for delivery to Duke Energy.[25] So the impact on seasonal peaks for Duke Energy can be viewed as representative of a utility that selects mostly solar power for its resource portfolio as opposed to also including wind power. However, renewable generation below the DCF was demonstrated during a few hours (less than 1 hour per year) in which the winter load was near or above the forecast annual peak. This observation supports the recommendation to balance solar with wind to ensure year-round reliability.

TVA is the only utility in which the summer "shortfall" for thermal generation is smaller than the winter "shortfall" for renewable generation, which indicates a risk for an 8 GW renewable energy generation scenario to cause a shift to a winter peaking situation. However, the thermal generation data for TVA are for 2013 and do not include substantial changes in TVA generation anticipated to be in place over the next several years.

Besides the winter "buffer" discussed above, another reason that solar energy is unlikely to result in greater reliability problems during "polar vortex" type events is that wind power is likely to be substantial during winter peaking episodes. As a result, the combined impact of solar and wind power during the very highest winter peak load periods is consistent with its DCF.

For example, TVA has experienced winter peaking conditions on average 11 hours per year over a 15 year period. In Figure 7, the power generation from an 8,000 MW portfolio of wind and solar is graphed for all 158 winter peaking hours. For hours with winter loads greater than 97% of the forecast annual

[22] Thermal generation capacity based on 2020 forecast for Duke Energy Carolinas, *Integrated Resource Plan* (September 2014); and Duke Energy Progress, *Integrated Resource Plan* (September 2014).

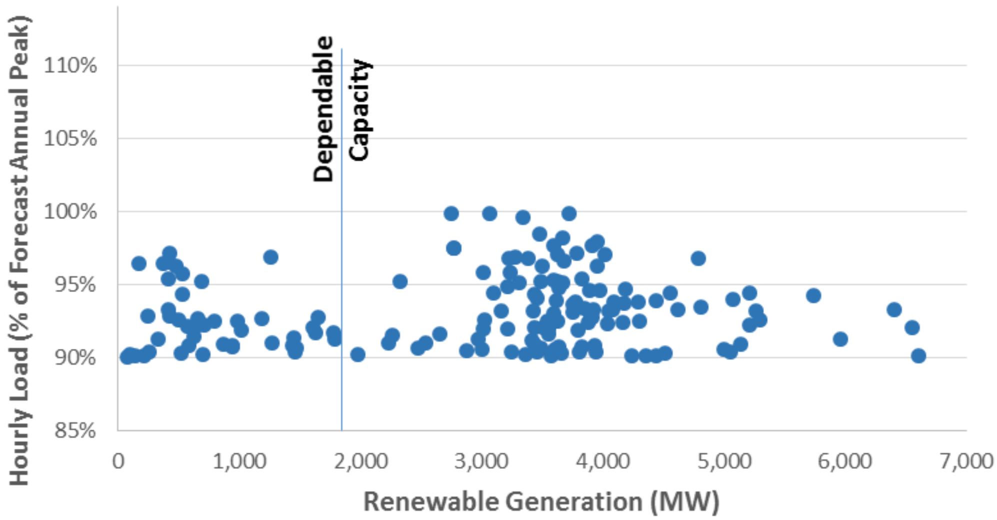
[23] Thermal generation capacity based on 2020 forecast for Southern Company, which is not available in a public document from Southern Company. This forecast was prepared for Southern Alliance for Clean Energy using public data by a consultant working on a confidential project.

[24] Thermal generation capacity based on January and August 2013 data for Tennessee Valley Authority, FERC Form 714 (Part 2, Schedule 2).

[25] Southeast Regional Transmission Planning Process, *2014 Economic Planning Studies: Preliminary Results* (September 2014).

peak, the renewable generation has capacity factors of approximately 40-60%. While wind and solar generation is likely to be very low during some winter peaking hours, since those hours are less than 97% of the forecast annual peak, the impact on reliability turns out to be consistent with conventional system risk standards.

Figure 7: Renewable Generation (8,000 MW Wind and Solar) vs TVA Load During Winter Peak Hours, 1998-2012



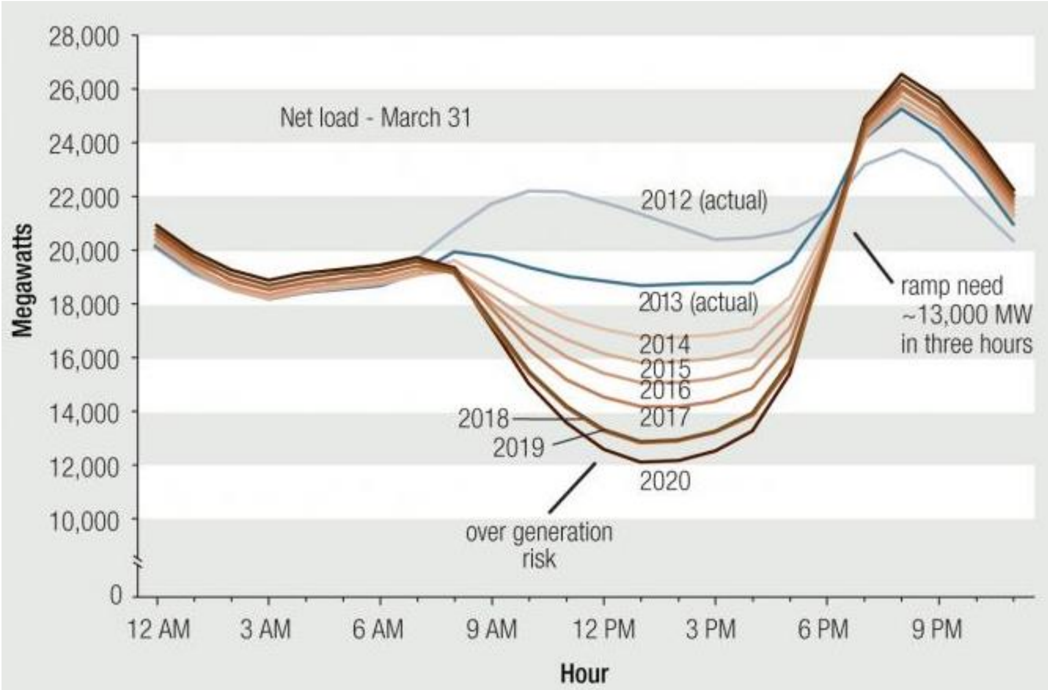
5. Impact of Renewable Energy on the Ramping of Conventional Generation Plants[26]

No discussion about renewable energy and the ability of utilities to adapt to utility resource planning can be complete without a reference to the widely cited California ISO "duck curve."[27] As illustrated in Figure 8, CAISO has forecast that the growing deployment of solar power in its transmission region will lead to episodes with large, rapid ramps during late afternoon hours as solar production rapidly ends. Because it illustrates the potential for renewable generation to drive a ramp rate of over 4 GW per hour in the springtime, the graph has generated widespread concern about the impact of renewables on utility system operations.

[26] See Attachment C for more detail on this topic.

[27] California ISO, *What the Duck Curve Tells Us About Managing a Green Grid´* (2013).

Figure 8: Example of the Widely-Circulated California ISO "Duck Curve"



This graph, and others similar to it, have been circulated by senior utility executives in the Southeast.[28] However, the CA-ISO "duck curve" is not representative of conditions that are likely to occur in the Southeast, even at renewable energy deployment of 10-20% of annual electrcity demand.

In the Southeast, renewable energy generation will not cause any net increase in the ramping of convention generation in the near future. At levels of renewable energy deployment up to at least roughly 20% of annual peak demand, the following observations were made in this analysis:

- While some individual hours might have increased ramps, other hours will have decreased ramps.
- Large, rapid ramps will not become more frequent or severe due to solar power deployment.
- Substantial deployment of wind power will drive some increase in the frequency of ramping events, but will not cause a new class of large ramp rates.
- In general, solar power provided reliable on-peak power that tracks well with system peaks. While its impact does diminish as resource deployment becomes larger, that effect is gradual, predicable and manageable.

To reach these findings, the utility ramp rates should be put into perspective. The vast majority of utility ramp rates, <u>with or without</u> up to the maximum 8 GW of renewable energy analyzed here, remain below 5% of total system capacity. The idea that installing renewable energy with a nameplate capacity as great as 20% of total system capacity will lead to wide swings in operating loads is not supported by the data.

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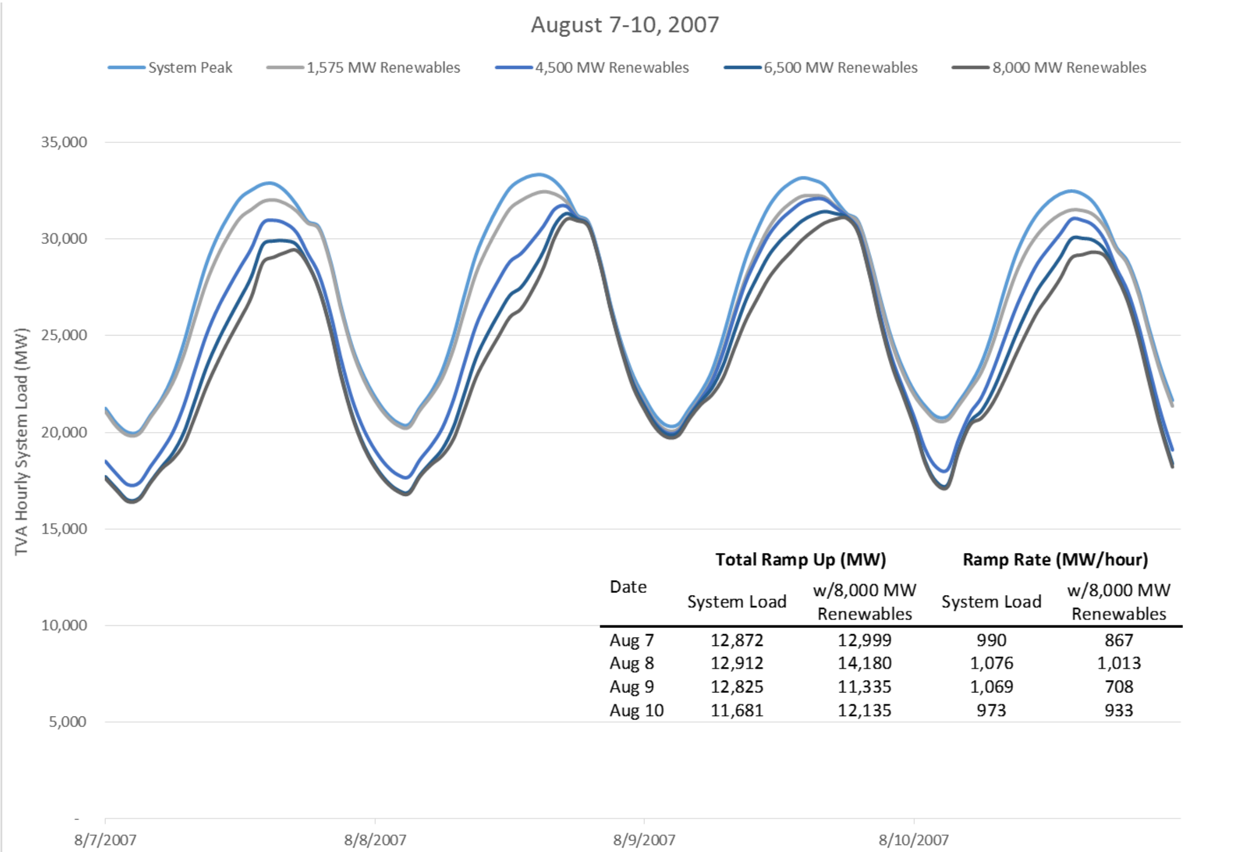
[28] Hoagland, J., *Utility Planning Challenges*, Tennessee Valley Authority, Presentation to Tennessee Advanced Energy Business Council Webinar (August 15, 2014).

Instead, the main result of adding renewable energy into a ramp rate analysis is that some hours have increased ramps, and other hours have decreased ramps. To illustrate extreme operating conditions, two episodes were selected from each utility dataset.

The first episode was selected to represent a system peaking event, identifying a multi-day period with peaks in excess of the utility's forecast annual peak.[29] Coincidentally, for all three utilities, the August 7-10, 2007 episode was selected as a highly challenging peaking event. The TVA case study, illustrated in Figure 9, provides a good example of how substantial levels of renewable energy could affect utility systems in the Southeast during challenging summertime hours.

Figure 9: TVA Load Shape, 0 – 8 GW Renewable Energy Scenarios, Summer Peak Episode



Date	Total Ramp Up (MW) System Load	Total Ramp Up (MW) w/8,000 MW Renewables	Ramp Rate (MW/hour) System Load	Ramp Rate (MW/hour) w/8,000 MW Renewables
Aug 7	12,872	12,999	990	867
Aug 8	12,912	14,180	1,076	1,013
Aug 9	12,825	11,335	1,069	708
Aug 10	11,681	12,135	973	933

Similar case studies for the other two utilities are provided in Appendix C. As summarized in Figure 10, adding renewable energy generally decreased the system swing on each day of the episode (ramp up from minimum load to maximum load) and also decreased the maximum ramp rate (averaged over the ramping period). There were some exceptions: TVA and Southern Company's maximum swing increased when renewables were added, but their minimum swing and ramp rates decreased. At the system level,

[29] Each of the six case study episodes span almost the full range of potential renewable energy generation. The Southern Company and TVA scenarios include substantial amounts of both solar and wind resources; average renewable generation capacity factors are about 40% in system peaking events and 50% in low load events. Because the Duke Energy analysis includes mostly solar resources, the average renewable generation capacity factors in the system peaking event and the low load event are lower, about 35%.

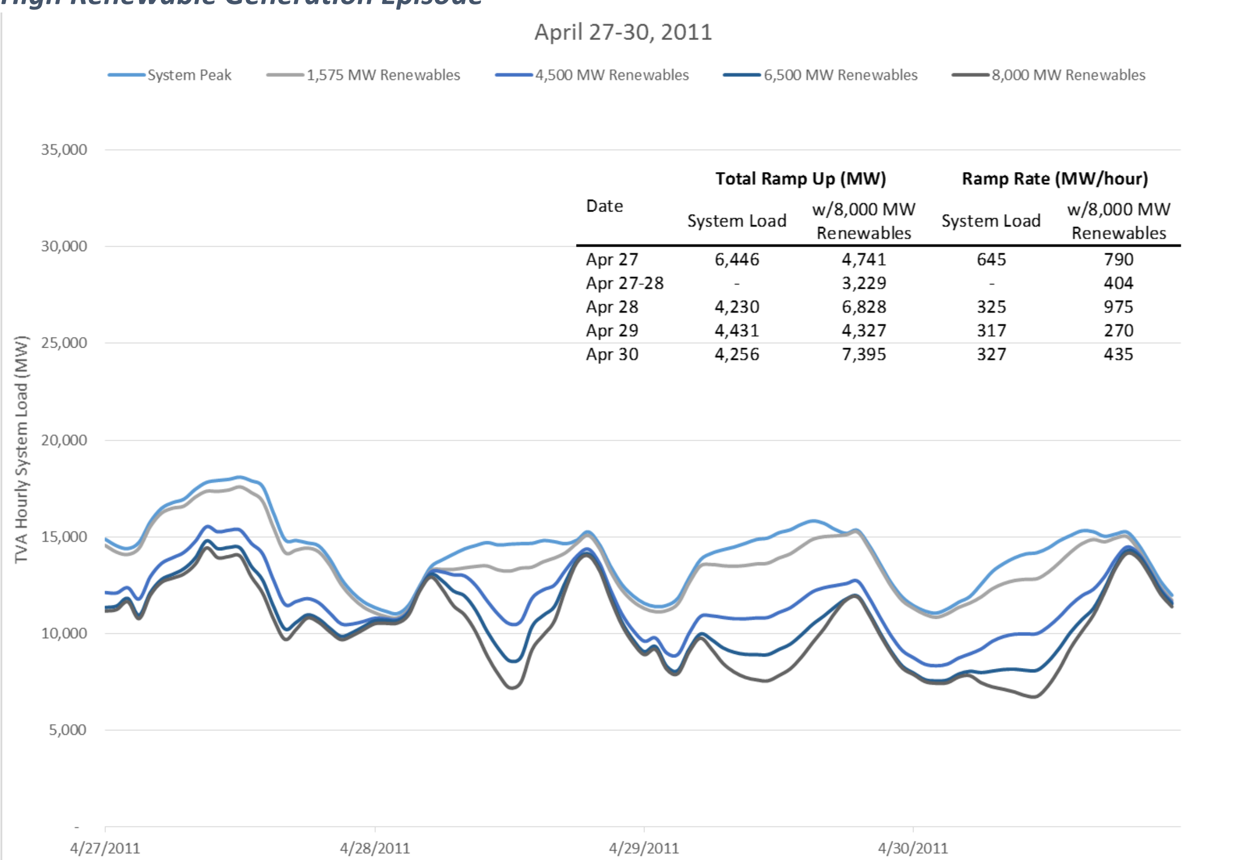
the case studies illustrate how adding renewables will often make system peaking events less challenging to utility operators.

Figure 10: System Peaking Event Case Studies

	System Peak (MW)	Minimum Swing (MW)	Maximum Swing (MW)	Maximum Ramp (MW/hr)
Duke Energy (North and South Carolina)	34,323	12,614	14,225	1,271
Southern Company	36,029	13,100	13,674	1,140
Tennessee Valley Authority	33,315	11,681	12,912	1,076
High Renewable Generation Scenario				
Duke Energy (North and South Carolina)	32,223	10,125	12,632	902
Southern Company	34,217	11,242	14,447	1,032
Tennessee Valley Authority	31,034	11,335	14,180	1,013

The second episode was selected to represent a low load event with high renewable energy generation. The most challenging low load events for each utility occurred in April, but on different dates in 2011 and 2012. The TVA case study, illustrated in Figure 11, provides a good example of how substantial levels of renewable energy could affect utility systems in the Southeast during low load periods with high renewable generation.

Figure 11: TVA Load Shape, 0 – 8 GW Renewable Energy Scenarios, Springtime Low Load / High Renewable Generation Episode



Date	Total Ramp Up (MW): System Load	Total Ramp Up (MW): w/8,000 MW Renewables	Ramp Rate (MW/hour): System Load	Ramp Rate (MW/hour): w/8,000 MW Renewables
Apr 27	6,446	4,741	645	790
Apr 27-28	-	3,229	-	404
Apr 28	4,230	6,828	325	975
Apr 29	4,431	4,327	317	270
Apr 30	4,256	7,395	327	435

As summarized in Figure 12, the swings and ramp rates experienced with or without renewables during springtime low load events are substantially less than those experienced during system peaking events. However, adding renewables does drive several noteworthy changes during low load events, including:

- Generally increases the size of daily swings.
- Can cause the system to add a second daily minimum/maximum, particularly if wind resources are not added to balance the solar resources. For TVA and Southern Company (with wind balancing solar), an additional minimum/maximum event was added on only one day. But for the Duke Energy scenario (with mainly solar resources), additional minimum/maximum events were added on each day of the episode.
- Generally increases the ramp rates – but the ramp rates still remain significantly lower than those experienced during system peaking events.

Overall, it would be fair to conclude that adding renewable energy would increase operational challenges during springtime low load events. But it would also be important to note that the operational responses challenges would remain significantly less challenging than those needed to manage system peaking events.[30]

Figure 12: Springtime Low Load / High Renewables Event Case Studies

	System Peak (MW)	Minimum Swing (MW)	Maximum Swing (MW)	Maximum Ramp (MW/hr)
Duke Energy (North and South Carolina)	17,857	3,307	6,616	641
Southern Company	21,062	3,405	7,702	804
Tennessee Valley Authority	17,975	4,230	6,446	645
High Renewable Generation Scenario				
Duke Energy (North and South Carolina)	17,857	2,220	5,616	891
Southern Company	18,458	4,897	7,671	979
Tennessee Valley Authority	14,432	3,229	7,395	975

To place these case studies in context, the entire data set was examined statistically for individual resources as well as the combined resource scenarios. Ramp rates were calculated over 1 hour increments.[31] This provided a broad view, considering hours in which renewable energy improved system ramp rates as well as those in which ramp rates became more challenging.

The statistical analyses demonstrates that solar power deployment will not cause an increase in the frequency or severity of hourly ramp rates, even when nameplate solar capacity represents as much as one-third of peak system demand. One reason for this finding is that the sun is almost always shining during peak hours. For example, on the TVA system, solar systems can produce at least 45% of nameplate capacity during 99% of the highest demand hours. The idea that solar might suddenly

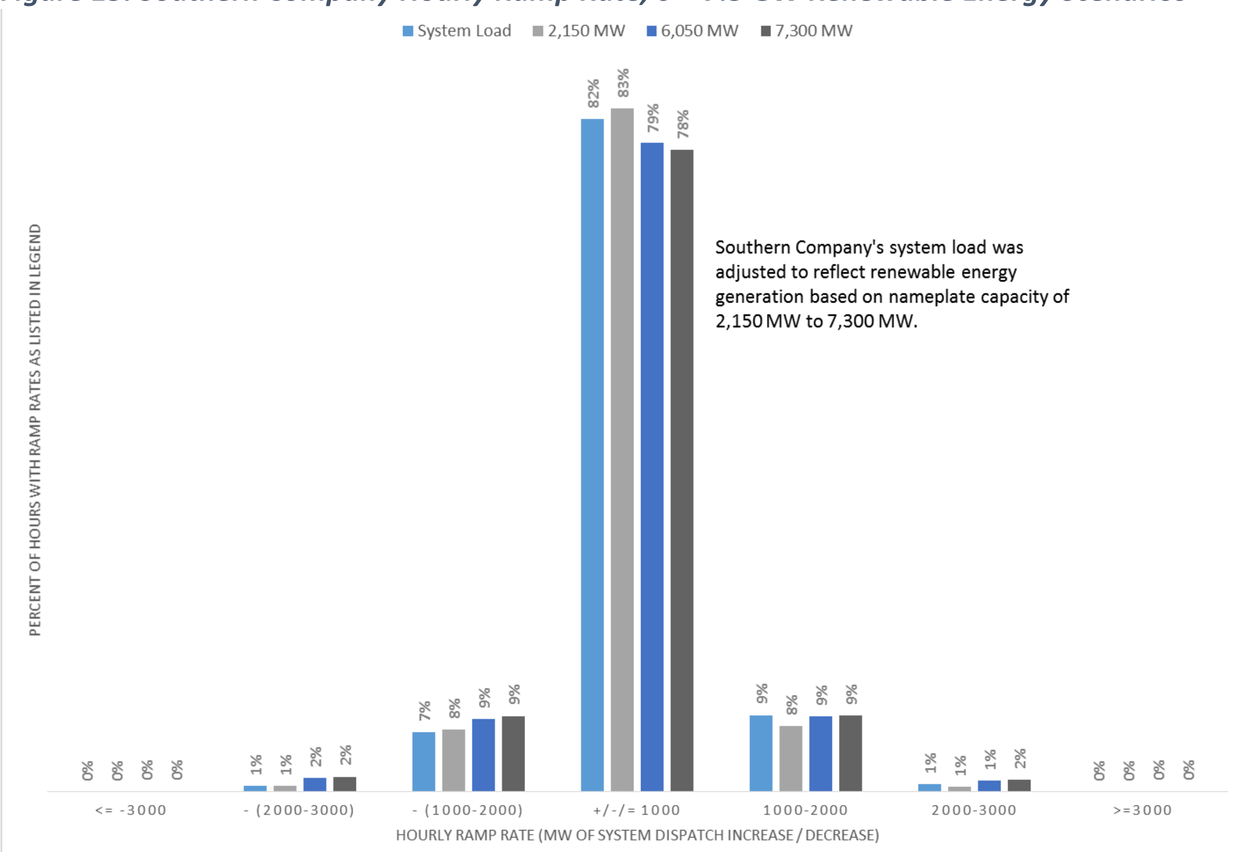
[30] As noted throughout this document, the analysis was restricted to the system level and did not include consideration of localized issues that might require dispatch or transmission contingency planning.
[31] Three hour ramp rates were also calculated for a portion of the analysis, but the results were not sufficiently different from the one hour ramp rate studies to suggest any benefit to more extensive study.

disappear from the TVA system during a peak demand period is simply not supported by careful analysis.

Wind power resources (including both in-region and imports via HVDC) will drive some increase in the frequency of ramping events. The main impact appears to be in terms of ramping the system down at a greater frequency. Fortunately, this impact can be mitigated by introducing contract terms that provide the utility with the opportunity to curtail wind generation to allow for other resources to be ramped down more gradually (after a brief curtailment, the wind generation would be restored to full output). The analysis also shows that wind power will not challenge system operators with a new class of large ramp rates, even when nameplate wind capacity represents as much as one-third of peak system demand.

Examined in combination (as is likely to occur in practice), higher levels of solar and wind energy deployment are likely to result in an increase in the frequency of higher ramp rates. For example, as illustrated in Figure 13, initially with the introduction of solar resources, the frequency of high ramp up rates decreases. The main adverse impact on ramp rate frequencies on the Southern Company system relates to the introduction of HVDC wind resources, but the impacts are relatively modest. As this example suggests, the increase in the frequency of hourly ramp rates in excess of 1,000 MW per hour is likely to be gradual and predictable.

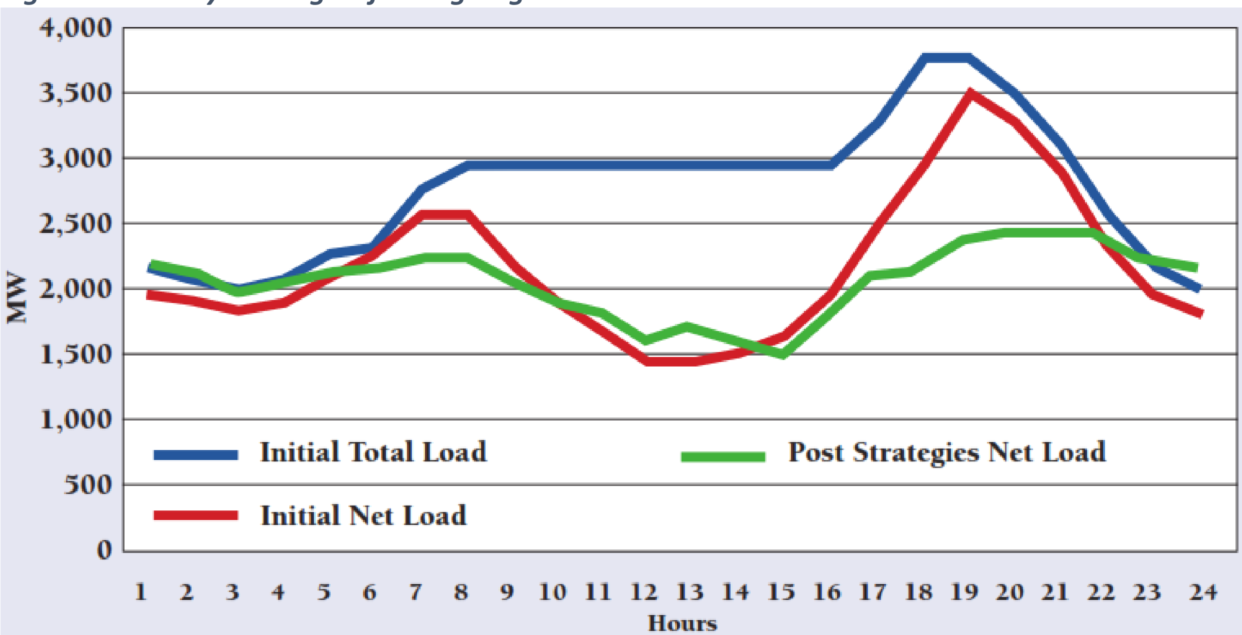
Figure 13: Southern Company Hourly Ramp Rate, 0 – 7.3 GW Renewable Energy Scenarios



Because any adverse impact on ramp rates will be gradual, predicable and not fundamentally different from existing operating conditions, utilities should find these changes manageable. To the extent that the increase in the *number* of hours with higher ramp rates is a concern, there are a number of readily available strategies that utilities could implement to better align load to variable renewable energy resources. Although no single strategy is a "silver bullet," a recent report by the Regulatory Assistance Project explains how several steps taken in combination, could allow utilities to nearly flatten load (see Figure 14).[32] The effectiveness of those steps for specific Southeastern utilities is not examined in this analysis, but certainly utility decisions to adopt (or reject) renewable energy resources should not be made without considering the combined effect of operational strategies.

In the Southeast, the California "duck" won't hunt. Quite simply, solar production and system demand are more fortunately aligned in the Southeast than in California. Geographic and system-specific factors result in the Southeastern solar resource actually *reducing* system ramp rates, at least up to a point. Concerns illustrated by the California ISO "duck curve" are surely valid in California, when it reaches much higher deployment of renewable energy generation than the Southeast is currently contemplating. Not only do these conditions not exist in the Southeast, the east-west orientation of load and other attributes of geography and weather mean that the "duck won't hunt" in the Southeast.

Figure 14: Utility Strategies for Aligning Load to Variable Resources



6. Remaining Uncertainties About Operational Constraints and Attributes Associated with Renewable Energy Development in the Southeast

While introducing substantial amounts of variable resources into a utility system represents real change for Southeastern utility systems, this analysis illustrates methods that utilities could use to plan for and manage the transition to renewable energy. For utilities to fully incorporate these findings into their planning practices, several additional steps, requiring access to confidential utility data, would be necessary.

[32] Lazar, J., *Teaching the "Duck" to Fly*, Regulatory Assistance Project (January 2014).

First, the System Peak Hours (SPH) method utilized for this analysis should be validated in comparison with a full Effective Load Carrying Capacity (ELCC) study. While the ELCC study method may not be well-suited to forecasting if the operating characteristics of future generation fleets are too uncertain, both methods can be used to study historical conditions for benchmarking purposes.

Second, a formal reserve margin study could be conducted to guide the development of plans to ensure that the introduction of large scale renewable energy would not adversely affect system reliability. This would effectively combine the results of a system planning study, a generation forecast study and the application of the SPH (or ELCC) method to assess the overall reliability of future generation fleets.

It is also worth acknowledging that these results may or may not be generalized to other Southeastern utilities. SACE plans to extend these analyses to include utilities in peninsular Florida and smaller utilities elsewhere in the Southeast. To the west or north of the utilities studied, regional authorities such as PJM have adopted means of analyzing renewable energy resource to ensure reliable system operations.

Southern Alliance for Clean Energy November 2014

Project directed by John D. Wilson, MPP, Research Director with contributions by David Roman, Charlie Coggeshall, and Simon Mahan.

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Appendix A

System Peak Hours Method: Dependable Capacity Factor Analysis for Generic Renewable Energy Resource Development in the Southeast

In determining whether a utility has adequate resources to meet its forecast system requirements, Southeastern utilities appear to have adopted capacity factor-based approximation methods for measuring the dependable capacity factor (DCF) of renewable energy resources. (Elsewhere these may be referred to as an on-peak capacity value, a generation capacity credit, or by some other nomenclature.)

A capacity factor-based approximation method is the easiest, but least sophisticated method for measuring the DCF of variable renewable resources. A number of different methods for this measurement have been developed and applied, suggesting that utility planners have not coalesced around an ideal balance between simplicity and sophistication. The National Renewable Energy Laboratory (NREL) has categorized these methods into four groups, as summarized in Figure 1, of which the preferred metric for measuring the DCF is the effective load carrying capability (ELCC) method.

Figure 1: Approaches to Measuring the Dependable Capacity Factor for Variable Renewable Energy Resources, in Order of Increasing Difficulty[1]

Name	Description	Tools Required
1. Capacity factor approximation using net load	Examines RE output during periods of highest net demand	Spreadsheet
2. Capacity factor approximation using loss of load probability (LOLP)	Examines RE output during periods of highest LOLP	Spreadsheet
3. Effective load-carrying capacity (ELCC) approximation (Garver's Method)	Calculates an approximate ELCC using LOLPs in each period	Spreadsheet
4. Full ELCC	Performs full ELCC calculation using iterative LOLPs in each period	Dedicated tool

The more difficult methods require use of loss of load probability (LOLP) data. LOLP is a probability estimate of how often the load on a power system is expected to be greater than the capacity of the generating resources. LOLP data are derived from, among other data, a "complete inventory of conventional generation units' capacity, forced outage rates and maintenance schedules."[2] With Southeastern utilities in significant flux, considering a high number of ongoing plant retirements and new generation in process, it is impractical for a non-utility planning study to obtain a useful forecast with a "complete inventory" of these data. Even for a utility planning department, creating such a

[1] Denholm, P. et al., *Methods for Analyzing the Benefits and Costs of Distributed Photovoltaic Generation to the U.S. Electric Utility System*, National Renewable Energy Laboratory, NREL Technical Report NREL/TP-6A20-62447 (September 2014), p. 29.
[2] Keane, A. et al., "Capacity Value of Wind Power," *IEEE Transactions on Power Systems* (v. 26, no. 2), Task Force on the Capacity Value of Wind Power, IEEE Power and Energy Society (September 2010), p. 3.

forecast prior to committing to a particular resource plan may be too resource intensive. Thus, an methods that require LOLP data may not be the best tool for long-term planning studies.

However, In reviewing the methods used by Southeastern utilities for measuring DCFs, to the extent those methods have been publicly explained, it appears that do not capture both the short term and the annual variability of renewable energy resources, particularly their correlation with demand in a variety of circumstances over a multi-year period.[3] In order to address this shortcoming without engaging in an impractical forecasting effort, a new variant of the capacity factor-based approximation method, the System Peak Hours (SPH) method, is applied to three vertically-integrated utilities in the Southeast. The SPH method is effective at capturing both the short-term (hourly) correlation with demand, as well as the annual variability of renewable energy resources. The SPH method improves on other capacity factor- based approximation methods by using a matched, multi-year set of renewable energy and utility system demand data.

1. Description of the System Peak Hours (SPH) Method

The System Peak Hours (SPH) method calculates dependable capacity factors (DCFs) that are a simple average of capacity factors during winter and summer peak hours. Peak hours are defined as hourly loads exceeding 90% of the forecast annual peak, with the number of hours included in this definition varying from year to year depending on how actual system demand relates to the forecast annual peak. The calculation is performed using a dataset that includes modeled (or actual, if available) capacity factors for renewable energy resource technologies and system loads for individual hours spanning several years, with the validity of the method increasing as the number of years included in the dataset becomes larger.[4]

The use of the forecast annual peak as the basis for selecting the peak hours is the *first* distinctive feature of the SPH method. Because the hours being selected are precisely those in which system demand is likely highest relative to available capacity, it is essential that the load and variable resource datasets be time-correlated. The importance of the correlation between the definition of peak hours and system capacity planning standards is that the definition should approximate the selection of hours with higher LOLP. Referring back to Figure 1, the SPH method does not fall neatly into either category of capacity factor-based approximation methods: it does not use highest net demand, because selection of high demand hours is relative to forecast demand, but neither does it rely on LOLP. The SPH method has characteristics of each category.

The SPH method follows a multistep calculation process – listed here - in order to estimate the DCFs associated with types of renewable energy resources. Note that each step in the method is also illustrated using a causal loop diagram approach, in Figures 2-5.

- Step 1: Representative load shapes of the different renewable resources (e.g., various solar and wind technologies) are estimated using modeled production load shapes. The modeled

[3] Keane (2010), p. 4.

[4] Using a larger number of years provides a wider range of climate, economic, and customer load conditions over which to test the potential interaction of renewable energy and system demand. The SPH method applied to very short time periods could generate unrepresentative results. The specific data coverage used in this analysis is discussed in Section 4.

production data should be specific to actual or reasonably feasible production sites[5] located in, near or proposed for interconnection with the service territory of the specific analyzed utility. The data used in this analysis are described in Section 4. Based on these site-specific, modeled production data, system capacity factors are calculated as a simple average annual capacity factor (and thus do not depend on the SPH method).

Peak hours are selected by comparing hourly system load to the utility's forecast annual peak. Hours with system load greater than 90% of the utility's forecast annual peak for the respective planning year are considered peak hours. The data are described in Section 4.

Seasonal DCFs are estimated individually, at each individual renewable energy production site, assuming no prior renewable energy development (existing system loads). Each DCF value is simply the average of capacity factors during the applicable peak hours.

The representative load shape (or production curve) for the generic system resources are created using a weighted (or simple) average of the hourly production data for each site-specific resource dataset. For the Tennessee Valley Authority (TVA) analysis, in order to select "best" sites to focus on resources that would be most preferred by the utility, sites were selected based on advantageous system capacity factor and DCFs. The selection criteria and averaging process should be reasonably transparent and related to the planning study objectives.

- Step 2: Average DCFs and net resource system loads are determined for the representative renewable resource load shapes. These representative resource load shapes are particularly useful for integrated resource planning studies, which typically constrain the number of resources considered in the modeling process and hence would not evaluate specific projects.

  The average DCFs for each resource technology are estimated individually in the same manner as described in Step 1 for the individual sites. The net resource system loads are determined by detracting from the system load shape the various resource hourly load shapes.

- Step 3: Seasonal DCFs for the renewable resource load shapes are calculated. Seasonal (winter and summer) DCFs are needed because most capacity planning models utilize a two-season capacity rating approach. In a utility planning context that applies a different capacity rating approach, the method should be adapted accordingly. The peak hours for these net system loads are selected using the same criterion as in Step 2.

- Step 4: Seasonal DCFs and dependable capacity supplied at a utility portfolio level are calculated by assuming specific levels of resource deployment (tranches) over time. However, rather than using the utility's forecast annual peak, a seasonally modified net annual peak is used. The peak is adjusted downward, taking into consideration the seasonal dependable capacity supplied by the renewable energy resources and also the need to ensure that those resources are augmented by the utility's reserve margin (typically 15%). A minimum of three tranches of

[5] The sites should be representative of likely resources that the project developers and the utility would be more likely to develop during the planning period in which the DCFs will be used. So for example among a random sample of solar production sites, a cross-section of sites with advantageous annual capacity factors and on-peak production should be used.

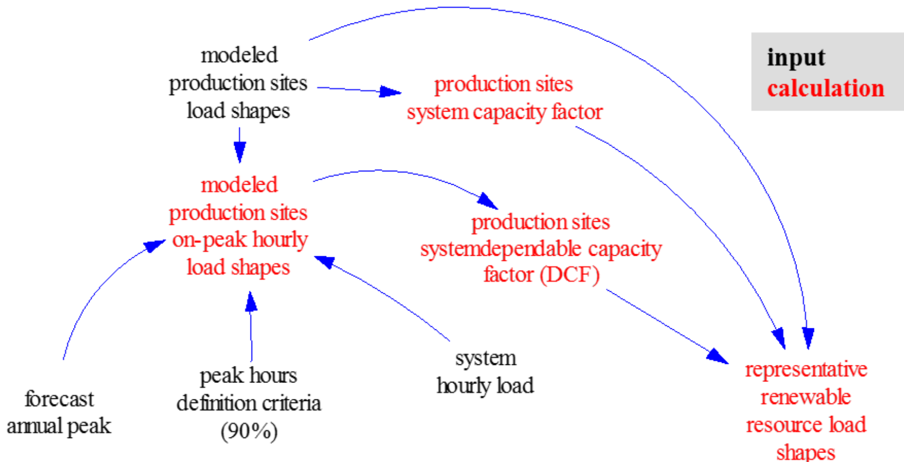
renewable resources development have been considered for all analyzed utilities, as described in Section 6.

The seasonal modification of the forecast net annual peak is the *second* distinctive feature of the SPH method. The seasonally modified net peak is particularly important because, as solar power is developed to scale, the net system peak may shift from primarily summer afternoon hours to include more summer evening and winter morning hours. Since the output of solar systems is relatively small (or zero) during those hours, the contribution of solar power to meeting system peak needs would be diminished. Thus, in Step 4, the forecast annual peak is modified for winter and summer periods as the forecast annual peak, minus the seasonal net dependable capacity for the renewable energy resources included in the scenario, minus the portion of the seasonal net dependable capacity needed to meet reserve margin requirements (typically 15%).

Another reason it is important to produce distinct summer and winter dependable capacity ratings for renewable energy resources is to ensure consistency with the manner in which conventional resources are planned. Currently, many planning regions (even those using the ELCC method) calculate only a single, year-round ELCC measurement for renewable energy resources. Yet for conventional, thermal generation resources, it is standard practice to calculate seasonal capacity ratings on a resource-specific basis. As discussed below, the seasonal capacity rating for solar is higher in summer than in winter, but for wind the reverse is true. Thus, the SPH method can be used to ensure that a utility considers the attributes of each resource, whether variable or conventional thermal, using consistent methods.

The seasonal net dependable capacity is calculated as the product of the seasonal net dependable capacity factor and the nameplate capacity of the renewable energy resources included in the scenario. Because the seasonal net dependable capacity factor is the result of this process, the calculation process is iterative until a stable solution is found.

Figure 2: Step 1 - Representative Renewable Resources Load Shapes Estimation

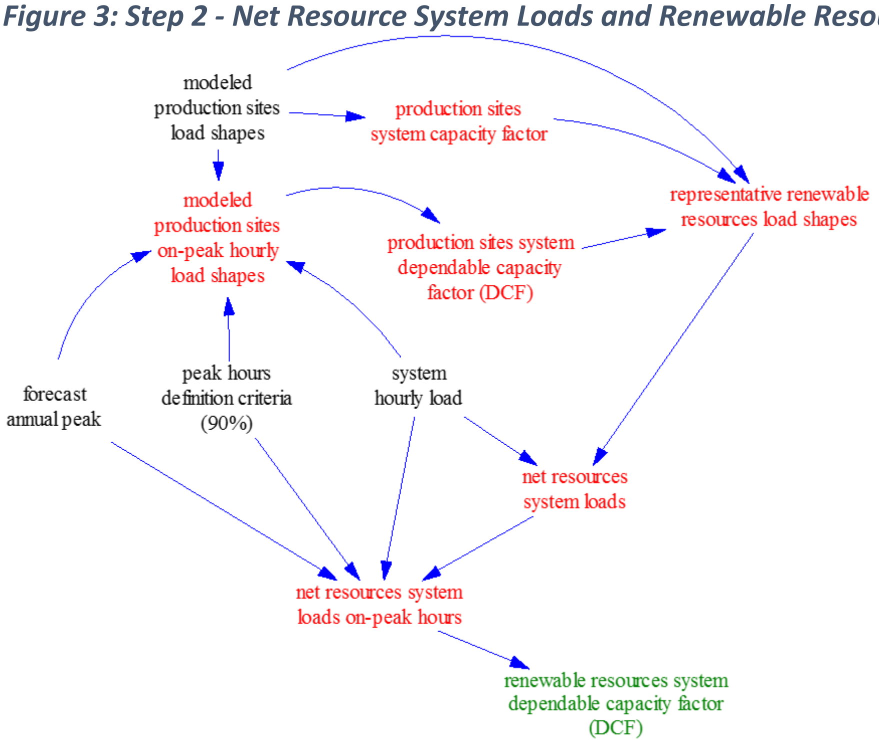


a) Based on modeled production sites load shapes, system capacity factors associated to the individual sites are calculated (and thus do not depend on the SPH method).

b) Peak hours are selected by comparing hourly system load to the utility's forecast annual peak. Hours with system load greater than 90% of the utility's forecast annual peak for the respective planning year are considered peak hours. According to this peak hour selection, specific production sites dependable capacity factor (DCF) are estimated.

c) Finally, using as selection criteria the sites' system capacity factors and dependable capacity factors previously calculated, the representative load shapes of the different renewable resources are estimated as an average load shape of selected modeled production sites load shapes.

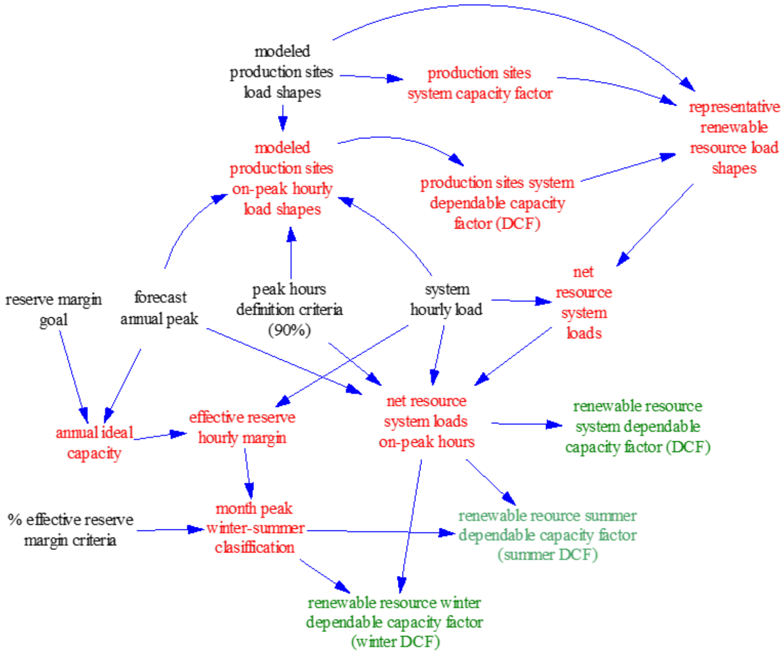
Figure 3: Step 2 - Net Resource System Loads and Renewable Resource System DCF Calculation



a) System average dependable capacity factors are determined for the representative renewable resource load shapes. The DCFs for each resource technology are estimated in the same manner as described in Step 1 for the individual sites as the average of capacity factors during the applicable peak hours.

b) The net resource system load is determined by detracting from the system load shape the renewable resource load shape.

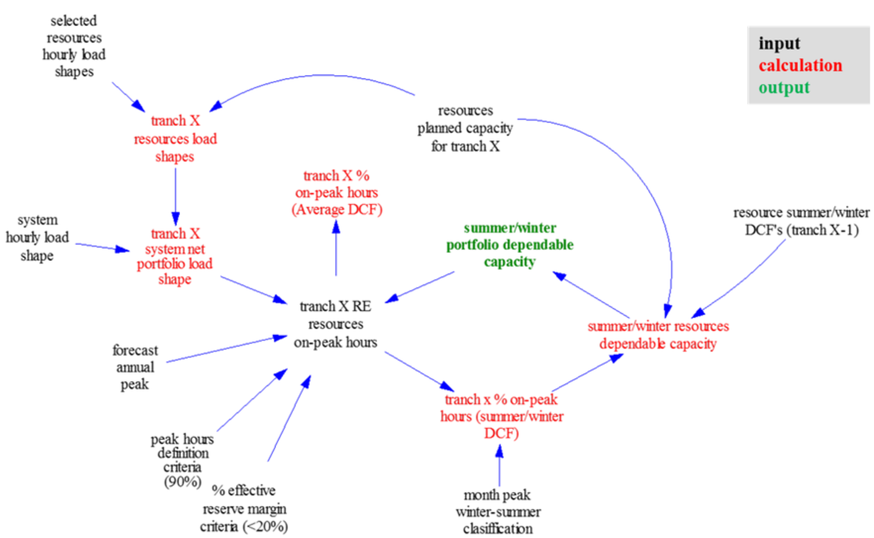
Figure 4: Step 3 - Renewable Resource Seasonal DCFs



Seasonal dependable capacity factors at a renewable resources level are calculated.

The peak hours for these net system loads are selected using the same criterion as in Step 2.

Figure 5: Step 4 - Portfolio DCFs & Average Capacity Deployed Calculation



Seasonal dependable capacity factors (DCFs) and dependable capacity supplied at a utility portfolio level are calculated by assuming specific values of deployment of individual resources through time.

However, rather than using the utility's forecast annual peak, a seasonally modified annual peak is used. The peak is adjusted downward, taking into consideration the seasonal dependable capacity supplied by the renewable energy resources and also the need to ensure that those resources are augmented by the utility's reserve margin (typically 15%).

The resulting adjusted peak might be thought of as an effective forecast peak for other energy resources besides those being studied. A minimum of three scenarios of renewable resources development (Tranches) have been considered for all analyzed utilities, as described in Section 6.

2. Need for a Balanced Method of Establishing Dependable Capacity for Renewable Energy Resources

Utilities plan for a target reserve margin that is designed to minimize the overall cost of reliability to the customer. The target reserve margin is an optimal value: insufficient reserves put customers at risk of either system failures or expensive short-term market purchases, but excessive reserves guarantees that customers will pay for capacity that may not be utilized sufficiently to justify the cost.

As with all energy resources, renewable energy resources contribute to a centrally planned utility's capability to plan for reliable service. Even though variable resources cannot be dispatched to meet increased demands for power,[6] wind and solar resources are often productive during system peak hours and thus contribute to the system's capacity to serve load. The question that the ELCC, SPH and other methods seek to answer is simply "How much conventional capacity can be avoided by the renewables?"

Because most utilities maintain relatively up-to-date reserve margin studies, their target reserve margins already incorporate consideration of these factors for the existing mix of generation resources and the characteristics of the utility systems' customer demand. The SPH method assumes a ceteris paribus approach, where the LOLP is unaffected by any changes to the characteristics of the generation mix or customer demand that occur other than the introduction of renewable energy resources. This is similar to the ELCC method, which holds all other aspects of the system constant, while calculating the difference in loads that can be reliably served by a generation system "with" and "without" a defined level of renewable energy resources.[7]

The SPH method approximates the same basic result: the DCF for each resource is equivalent to the amount of conventional capacity that would not be needed for the generation system to perform at the target reserve margin level. It is important to establish a DCF that is less than the nameplate value of the resource since it is not possible for a variable resource to generate power at 100% of its nameplate capacity all of the time. It is of course also important to establish a DCF that is more than 0%, since the renewable energy resource contributes at least somewhat to meeting on-peak demands.

If the SPH or some other capacity factor-based approximation method is used, the choice of the averaging period for the renewable energy output is a critical decision. Of course, if an ELCC or some other LOLP-based method is available, then that would provide a basis for measuring the DCF on the basis of reliability data. But when averaging is used, a misleadingly high or low DCF measurement can be obtained by excluding (or emphasizing) certain hours that are important (or unimportant) for a reliability measure.

A utility that suggests its method is preferable because it is "conservative" would be reaching a mistaken conclusion. Using a DCF value that is too low would be suboptimal, in that the resulting planning decisions would lead to excess generation capacity on the utility system, at a cost to its customers. Subject to several caveats, the SPH method achieves a balance.

[6] Note that wind resources can be curtailed almost instantaneously. Thus it is inaccurate to refer to wind resources as strictly "non-dispatchable." Many utilities routinely utilize short-term wind curtailments (reductions in output) to help regulate system power fluctuations.

[7] MISO, *Planning Year 2014-2015 Wind Capacity Credit* (December 2013).

3. Calibration of the SPH Method

As mentioned above, the distinctive features of the SPH method are the use of the forecast annual peak as the basis for selecting the peak hours, and the application of a seasonally modified forecast net annual peak. Each of these features could be more finely calibrated by, or in collaboration with, a utility.

Both of these design features rest on the assumption that an "optimal" level of generation (or system capacity target) on a utility system is represented by the forecast annual peak plus the target reserve margin.[8] The SPH method depends on the degree to which the utility's forecast annual (net) peak represents the system size that the utility targets in its capacity planning process and thus represents at least a reasonable approximation of an "optimal" system.

One way in which this approximation could be inaccurate is the choice to use the utility's peak forecast from the prior year. Given the lag between a forecast capacity gap (difference between system capacity and a future target value) and construction of new resources, an earlier forecast might better represent utility decision-making. However, for this analysis, it was determined that the prior year forecast introduced the least complexity in interpretation. Nonetheless, a utility or regulator might reasonably select a different representation of the system capacity target.

Another potential error in the approximation method is that the threshold, 90% of forecast annual (net) peak demand, is somewhat arbitrary. This value was chosen to identify the hours in which load is near the assumed system capacity target, net of variable renewable energy capacity. When load is near the assumed capacity target for the system LOLP should increase (all other things being equal), and the utility is more likely to experience a reliability event during those hours. To calibrate the threshold, the SPH method should be benchmarked against the ELCC method to determine a correlated value (e.g., higher or lower than 90%).

A third way in which a utility or regulator could improve this method would be to use a seasonal, rather than annual, system capacity target. Most utilities in the Southeast use an annual capacity target, almost always corresponding to the summer value but perhaps occasionally the winter target. A seasonal system capacity target should take into consideration the variation of seasonal capacity ratings for the thermal generation fleet as well as the variability of seasonal loads.[9] Making this improvement would likely result in two counteracting changes. On one hand, the 90% threshold would likely be applied to a slightly higher system capacity rating for winter (reflecting greater thermal efficiencies), reducing the number of winter hours studied. On the other hand, for utilities with substantial customer use of electric resistance space and water heating, winter peaks may be somewhat more variable than summer in a way that is naturally considered in the ELCC method but would be missed in the SPH method. In other words, the LOLP for a given load might be higher in winter than in summer, indicating an increase in the

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[8] Another benchmark, the weather normalized annual peak, was considered and tested for use in this method in place of the forecast annual peak. However, weather normalized annual peaks are not readily available for most utilities. A better reason for selecting the forecast annual peak assumption is that it is more closely related to capacity planning methods than the weather normalized annual peak. Whatever "optimal" system benchmark is chosen, it should be a routinely calculated, objective value. For example, if hourly LOLP data are available, those values could be used to increase the sophistication of this method.

[9] Seasonal peak forecast values were not used because available capacity should be representative of the forecast annual peak regardless of season. For example, winter capacity should be equal to, or greater than, the forecast annual peak plus reserve margin, even if the forecast winter peak is smaller than the summer peak.

number of winter hours studied. Because addressing both of these considerations would cancel out to some extent, a seasonal refinement would likely have little overall impact on the DCFs for renewable energy resources, particularly in the context of the summer peaking utilities studied in this analysis.

4. *Description of Study Data*

A. Annual Peak Demand Forecast

Utilities file Federal Energy Regulatory Commission (FERC) Form 714 on an annual basis. This form includes a ten-year projection of peak demand. For this analysis, the annual forecast selected was the final forecast (for example, the 2010 peak demand forecast used in this project would be the one filed in 2009). For unknown reasons, FERC does not have forecasts for all years for some utilities.

- *Duke Energy:* Reflecting demand from Duke Energy Carolinas and Duke Energy Progress (or its predecessors) using FERC Form 714 data (1997-2012).
- *Southern Company:* Reflecting demand from Alabama Power, Georgia Power, Gulf Power, Mississippi Power and Savannah Power (when applicable) using FERC Form 714 data (2001-2012).
- *Tennessee Valley Authority:* FERC Form 714 for the periods 1997-2002 and 2007-2012. For the period 2003-2006, the FERC Form 714 peak demand forecast values were not available from FERC. Weather normalized peak values obtained from a TVA graph were used instead.

For the utilities studied in this project, the summer peaks were used in all cases because they were highest. As discussed in Section 6 of the report, the SPH method might be improved by utilizing winter peak forecast as well.

B. Hourly Load

FERC Form 714 also includes an annual report of system load on an hourly basis. One challenge with these data in general is that utilities follow different practices in dealing with daylight savings time, and even vary those practices from year to year somewhat. As discussed above, it is essential that the utility load data be accurately matched with renewable energy generation datasets.

For Duke Energy and Southern Company, the hourly load data sources were the same as discussed above in Section 4.A. During discussions with TVA staff regarding calculations related to this analysis, discrepancies were identified between TVA's internal data records and the data obtained from TVA's FERC Form 714 filings. TVA supplied a complete dataset covering 1998-2012, which was used in lieu of the FERC Form 714 filings.

C. Solar Power Output

SACE contracted with Clean Power Research to simulate hourly production for two PV fleets – a fixed fleet and a tracking fleet. Specific sites were selected by SACE to be geographically dispersed across utility service areas, typically located near existing thermal generation, load centers or major transmission system intersections.

- *Duke Energy:* 12 sites across service territory (see Figure 6(A)), studied as utility-scale projects

- *Southern Company:* 24 sites (see Figure 6(B)) studied as utility-scale projects, including 15 sites within the service territory, plus 9 sites in close proximity, subdivided into sites likely to be delivered to Georgia Power, and sites likely to be delivered to other Southern Company affiliates
- *Tennessee Valley Authority:* 26 sites across service territory (see Figure 6(C)), with 10 higher performing sites selected to represent those most likely to be developed as utility-scale projects and the "all sites" average for fixed mount systems selected to represent large commercial installations, typically 5 MW or smaller on large rooftops or adjacent to business facilities

Clean Power Research's simulation used its SolarAnywhere FleetView modeling services, standard resolution (10 km x 10 km x 1 hour resolution).

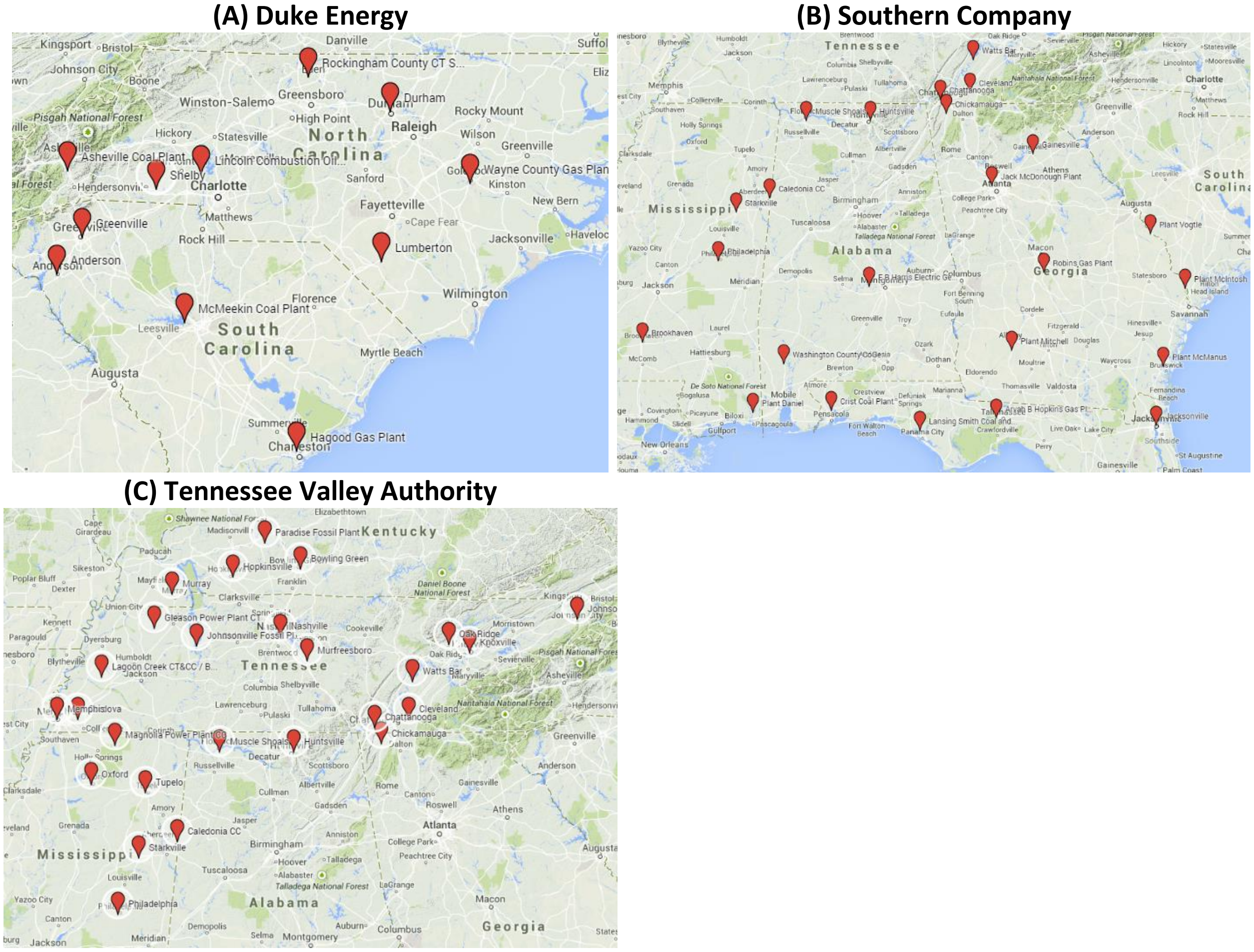
- Fixed tilt fleet: 1 MW_{AC}, south-facing, 20-degree tilt angle
- Tracking fleet: 1 MW_{AC}, N/S tracking axis, 0-degree tilt angle, tracking rotational limit of +/- 45°

All systems configured with 4,800 modules in 12 rows with a relative row spacing of 2.5 and combined DCPTC[10] rating of 1,200.5 kW. A general derate factor of 85% was used along with an inverter with a CEC weighted average efficiency of 98% and an albedo of 0.15.

Valid production data for smaller business and residential systems was not available for this project. Ideally, a simulated fleet of rooftop systems that takes into account the experience of other utilities and the typical roof designs of Southeastern buildings would need to be completed. An estimated cost for such an analysis was prepared by Clean Power Research to complement this study, but funding was not available from SACE or any utility to complete the analysis.

[10] Direct Current Performance Test Conditions. Note that other than this specific reference to direct current, all capacity and energy results are reported in alternating current (AC) results.

Figure 6: Solar Power Study Sites for (A) Duke Energy, (B) Southern Company and (C) Tennessee Valley Authority



D. Regional Wind Power Output

The Southern Wind Energy Association (SWEA) contracted with AWS Truepower to simulate hourly production for eight wind farm areas in the TVA service territory. The eight study sites, illustrated in Figure 7, were selected for study based on prior studies and data that identified good prospects. The study areas were not selected as specific locations that any company is developing a wind project, and during the selection, neither SACE nor SWEA solicited or received developer input of this type, nor were any particular environmental suitability screens applied.

The AWS windTrends national wind map is modeled at a 200 meter resolution and validated using a variety of surface station data. For the TVA analysis, AWS utilized a total of 89 validation points in the following states of interest: Tennessee, Alabama, Mississippi, Arkansas, Missouri, Kentucky, and North Carolina. Due to the interpolation of data from these points to the sites of interest, the results should not be considered indicative of sites at the exact locations, but of wind conditions in the general area of the sites included in the analysis. Based on review of relevant data and consultation with various experts, the resulting wind resource is a reasonable representation of modeled data that might result from a more extensive prospecting and site selection process.

Because wind developers will prospect for better sites, the TVA analysis uses the data associated with the five best sites rather than all eight sites. This does not mean that the areas associated with the three less attractive sites should be considered undevelopable; there may be geographic features in that region whose characteristics are not appropriately modeled at the resolution available in the AWS windTrends dataset.

Due to the expense associated with obtaining these data, data for sites located within the Southern Company or Duke Energy service areas were not purchased. For Southern Company, the five sites from the SWEA data sited closest to its service territory were selected as indicative of resources that might be available for direct interconnection with the Southern Company transmission system. Regional wind was not studied for Duke Energy due to lack of suitable data.

Figure 7: Wind Power Study Sites

E. HVDC wind-generated power imports

There are two proposed HVDC transmission projects anticipated to interconnect in the Southeast. Clean Line Energy Partners is developing the Plains and Eastern Line with a capacity of 3500 MW, connecting wind resources in or near western Oklahoma with TVA's Shelby Substation (near Memphis, TN).[11] Pattern Energy is developing the Southern Cross Line, connecting wind resources on the ERCOT system with TVA and Southern Company in Mississippi, with two phases of 1500 MW bidirectional capacity.[12] In turn, power from these projects can be wheeled through to other interconnected systems in the Southeast, subject to transmission constraints.

Limited generation data are available for these projects. Clean Line Energy Partners contracted with 3tier to simulate hourly production at two hypothetical wind farms in Oklahoma. Details of this study have been provided to TVA, and SACE was permitted to analyze these data subject to certain

[11] See http://www.plainsandeasterncleanline.com/site/home
[12] See http://www.southerncrosstransmission.com/

confidentiality protections. Wind industry experts were consulted and generally agree that similar wind profiles are likely to be available from the Texas Panhandle for supply to the ERCOT grid and then to the Southern Cross project. For this reason, the 3tier data were used as the basis for calculating the potential output from both proposed HVDC transmission projects.

Wind power delivered via HVDC transmission differs in important respects from power delivered through a direct interconnection with a utility transmission system. One difference is that the delivery constraint at the point of interconnection (e.g., TVA's Shelby Substation) is likely to be different from the peak power available from wind farms under contract for delivery. According to developers of both projects, it is likely that the transmission lines would "oversubscribe" their available capacity due to the basic business model for the project. During a few peak hours in which all wind farms under contract are operating at or very close to 100% of nameplate capacity, the transmission operator would need to utilize a contract clause to slightly curtail (or redirect) wind farm output to limit delivery to the operating constraint. While curtailments might appear to be costly, the cost would be compensated for during other hours in which the "oversubscription" would enable the transmission line to carry the "extra" power and thus increase revenues.

There are several other significant differences. Clean Line's HVDC technology may require a minimum throughput to maintain operating voltage. Pattern Energy's business model envisions bi-directional flows, with the potential for energy from the Southeast to be utilized within ERCOT. System rules in ERCOT also provide for a certain degree of advance planning and firming of power delivery. Finally, for power delivered via wheeling through another utility's transmission system, adjustments for additional line losses are necessary.

Each of these factors was addressed to the extent feasible in the development of the "as-delivered" HVDC wind power hourly capacity factors.

- *Duke Energy:* Consistent with input from various experts, the Clean Line HVDC resource was assumed, using oversubscription factors and a minimum delivery threshold selected by SACE to represent a likely business model. Line losses on the TVA system (used for wheeling) were set at 3% based on TVA practices. Due to anticipated transmission constraints, this resource was limited to 500 MW delivered.

- *Southern Company:* Clean Line and Pattern Energy's projects were modeled separately. The Clean Line HVDC resource was modeled the same as for Duke Energy except that no specific transmission delivery constraint was identified. Pattern Energy's project was modeled using oversubscription factors selected by SACE to represent a likely business model.

- *Tennessee Valley Authority:* Consistent with the preferences of TVA planners, a generic HVDC resource was created. The oversubscription factor and minimum delivery threshold were set at the average of those for the business plans assumed for the Clean Line and Southern Cross projects.

It should be emphasized that this resource characterization is not an attempt to model specific contract terms. Instead, the "as-delivered" characterization reflects operating constraints and opportunities in a likely business model that would form a *starting point* for negotiating specific terms and conditions that might establish operational guidelines.

5. Application of the SPH Method at Initial Stages of Renewable Energy Resource Development

The dependable capacity factors (DCF) for each resource, for each utility system, are summarized in

Figure **8**. As discussed in Section 1, the DCF is calculated as the simple average of capacity factors during winter and summer peak hours. Peak hours are defined as hourly loads exceeding 90% of the forecast annual reserve requirement, which is the forecast annual peak plus reserve margin.

Values are presented for winter, summer, and annual (planning year) periods. Because most utility resource planning models require distinct winter and summer capacity ratings for each resource, the annual DCF is provided mainly as reference to help illustrate the relative weight of each seasonal capacity rating. Each DCF is compared to the utility's current publicly-provided rating (if available). The annual capacity factor (CF) for each resource is also presented for comparison; these values area simple average (percent of rated annual MW_{AC} output), not requiring the SPH (or any other) method.

Because Southern Company's distribution utilities contract for power individually (although subject to a joint dispatch arrangement), DCF values for solar power were calculated separately for interconnection to Georgia Power Company and to the other three companies. This was also important due to the more advanced state of Georgia Power's adoption of solar power as discussed in Section 6 below.

Figure 8: Annual and Seasonal Dependable Capacity Factors, Assuming No Substantial Prior Renewable Energy Development

	Solar – Tracking	Solar – Fixed	Regional Wind	HVDC Wind Imports
Duke Energy (North and South Carolina)				
Annual CF	23%	21%	-	57%
Summer DCF	66%	56%	-	43%
Winter DCF	12%	10%	-	67%
Average DCF	63%	54%	-	44%
Duke Adopted DCF[13]	*46%*	*46%*	*13%*	*n/a*
Southern Company – Georgia				
Annual CF	24%	21%	-	-
Summer DCF	61%	51%	-	-
Winter DCF	23%	17%	-	-
Average DCF	61%	51%	-	.
Southern Company – Alabama, Mississippi & Florida				
Annual CF	24%	21%	38%	66% / 57%
Summer DCF	61%	53%	10%	46% / 56%
Winter DCF	16%	11%	36%	84% / 96%
Average DCF	60%	52%	10%[14]	47% / 57%[15]
Southern Adopted DCF	*n/a*	*n/a*	*n/a*	*n/a*
Tennessee Valley Authority				
Annual CF	23%	20% / 20%	38%	62%
Summer DCF	66%	56% / 53%	9%	53%
Winter DCF	14%	13% / 14%	36%	62%
Average DCF	60%	51% / 49%	12%	54%
TVA Adopted DCF	*68%*	*50% / 50%*[16]	*14%*	*14%*

[13] Duke Energy Carolinas, *Integrated Resource Plan* (September 2014); and Duke Energy Progress, *Integrated Resource Plan* (September 2014). For solar, an average of the DEC 46% and DEP 44% "contribution to peak load" value is used.

[14] Proxy data from sites in TVA service area, but close to Alabama Power or Mississippi Power service areas.

[15] Clean Line Energy's Plains & Eastern Line and Pattern Energy's Southern Cross HVDC projects reported separately. The differences are mainly due to losses imposed by intermediate AC transmission wheeling of the Clean Line power through TVA; Pattern Energy would be delivered directly. The underlying wind data are identical.

[16] For TVA, the first figure refers to utility-scale fixed mount solar systems, and the second figure refers to commercial-scale fixed mount solar systems. For TVA, the higher performing systems were concentrated in the western portion of the TVA system, so the "all sites" solar production data were used to represent commercial scale systems. For other utilities, higher performing systems were not as geographically concentrated so this distinction was not utilized.

6. Scenarios for Buildout of Renewable Energy Resource Development

One reason the SHP method was developed was to investigate the impact of large-scale renewable energy development on utility systems. As renewable energy resources are deployed at scale, the value they offer to the system as capacity resources changes.[17] The DCF of each individual resource is affected significantly by the deployment of any type of variable resource.

As a result of some of the initial calculations during the analysis, the renewable energy resource development scenarios were selected and studied consistent with these general patterns.

- DCF values for each specific solar resource (i.e., commercial-scale fixed mount solar systems) were affected by the total solar resources deployed, regardless of technology or type, because the performance of each solar resource technology was closely correlated with the others. (This is illustrated below, see Figure 11.)
- Solar tracking resources appeared highly advantageous in terms of DCFs relative to fixed mount systems. However, since the DCFs decline significantly (see Figure 11), it is assumed that while tracking systems might dominate utility-scale development during the early phases of development, fixed mount systems could predominate overall.
- DCF values for regional wind resources and HVDC wind resources were not as closely correlated, so are best thought of as distinct resources. (This can be seen by comparing Figure 12 with Figure 13.)
- Significant differences in DCF values occurred only after development of roughly a gigawatt (GW) of additional renewable energy (see Figure 12 and Figure 13).

Based on these patterns, as well as information about the schedules of various projects or utility regulatory proceedings, a renewable energy development scenario was developed for each utility in the study. For example, utility avoided cost proceedings typically occur on a biennial basis, so each utility scenario is expressed as three to four "tranches," representing blocks of renewable energy that could be developed in two or three year periods.

The scenarios were developed for each specific utility based on publicly available information about existing projects, potential projects and general industry trends. In general, the goal was to have a balanced portfolio of about 4,000 MW of solar and wind each. This was not precisely achieved due to the lack of suitable data for regional wind projects. The assumed solar and wind capacity levels for each scenario are presented in Figure 9.

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[17] Andrew Mills and Ryan Wiser, "An Evaluation of Solar Valuation Methods Used in Utility Planning and Procurement Processes," LBNL-5933E (December 2012).

Figure 9: Renewable Energy Development Scenarios (MW Nameplate Capacity)

	Solar – Tracking	Solar – Fixed	Regional Wind	HVDC Wind Imports	Total	Energy (Annual Capacity Factor)
Duke Energy (North and South Carolina)						
Tranche 1		1,089	-	-	1,089	1%
Tranche 2	1,000	911	-	500	2,411	4%
Tranche 3	500	500	-	-	1,000	1%
Duke Total	**1,500**	**2,500**	**-**	**500**	**4,500**	**6%**
Southern Company – Georgia						
Tranche 1	750	900	-	-	1,650	2%
Tranche 2	250	-	-	-	250	9%
Tranche 3	250	250	-	-	500	2%
Southern Company – Alabama, Mississippi & Florida						
Tranche 1	250	150	100		500	2%
Tranche 2	750	250	150	2,500[18]	3,650	9%
Tranche 3	250	250	250		750	2%
Southern Total	**2,500**	**1,800**	**500**	**2,500**	**7,300**	**13%**
Tennessee Valley Authority[19]						
Tranche 1	500	175 / 550	350	-	1,575	2%
Tranche 2	50	75 / 150	150	2,500	2,925	9%
Tranche 3	700	150 / 300	100	750	2,000	4%
Tranche 4	400	300 / 600	200	-	1,500	2%
TVA Total	**1,650**	**700 / 1,600[20]**	**800**	**3,250[21]**	**8,000**	**16%**

7. Application of the SPH Method with Large Scale Renewable Energy Resource Development

Utilizing the scenarios described above, the resulting DCFs can be specified on a summer and winter basis. (The calculation method is described in Section 1, Steps 4-6) The DCFs calculated for Tranche 1 applies the SPH method with no adjustment to load shape. Beginning with Tranche 2, the load shape is adjusted to net out the effects of the resources included in Tranche 1, and so forth.[22] As a result, the DCF used for a specific technology resource in subsequent tranches is typically lower than for the same resource included in the first tranche.

[18] Clean Line Plains & Eastern: 1500 MW; Pattern Energy Southern Cross 1000 MW.

[19] For the TVA analysis, existing Midwestern wind contracts were not studied because data regarding their hourly production were not available. TVA applies a 14% dependable capacity factor for existing resource contracts.

[20] The first figure refers to utility-scale fixed mount solar systems, and the second figure refers to commercial-scale fixed mount solar systems. See note 16.

[21] This value assumes that the imports are sourced equally from the two proposed HVDC projects.

[22] A degree of regulatory lag, similar to what occurs in avoided cost proceedings, is assumed in the DCF calculation. So the DCF established for Tranche 2 represents a midpoint prior to the full completion of Tranche 1 and so forth.

Figure 10: Dependable Capacity Factors, Using Renewable Energy Development Scenarios

Summer DCFs	Solar – Tracking	Solar – Fixed	Regional Wind	HVDC Wind Imports
Duke Energy (North & South Carolina)				
Tranche 1	66%	56%	-	43%
Tranche 2	51%	39%	-	35%
Tranche 3	44%	34%	-	37%
Southern Company – Georgia				
Tranche 1	61%	51%	-	-
Tranche 2	40%	30%	-	-
Tranche 3	34%	24%	-	-
Southern Company – Alabama, Florida & Mississippi				
Tranche 1	61%	53%	10%	46% / 56%[23]
Tranche 2	41%	32%	12%	23% / 29%
Tranche 3	35%	27%	12%	22% / 28%
Tennessee Valley Authority				
Tranche 1	66%	56% / 54%[24]	9%	53%
Tranche 2	56%	45% / 43%	9%	28%
Tranche 3	48%	37% / 36%	10%	22%
Tranche 4	39%	29% / 27%	11%	21%

Winter DCFs	Solar – Tracking	Solar – Fixed	Regional Wind	HVDC Wind Imports
Duke Energy (North & South Carolina)				
Tranche 1	12%	10%	-	67%
Tranche 2	6%	5%	-	58%
Tranche 3	5%	4%	-	60%
Southern Company – Georgia				
Tranche 1	23%	17%	-	-
Tranche 2	6%	4%	-	-
Tranche 3	4%	3%	-	-
Southern Company – Alabama, Florida & Mississippi				
Tranche 1	16%	11%	36%	84% / 96%[23]
Tranche 2	3%	2%	32%	37% / 45%
Tranche 3	2%	1%	28%	33% / 38%
Tennessee Valley Authority				
Tranche 1	14%	13% / 14%[24]	37%	63%
Tranche 2	8%	7% / 7%	34%	28%
Tranche 3	4%	4% / 4%	35%	16%
Tranche 4	3%	3% / 3%	34%	20%

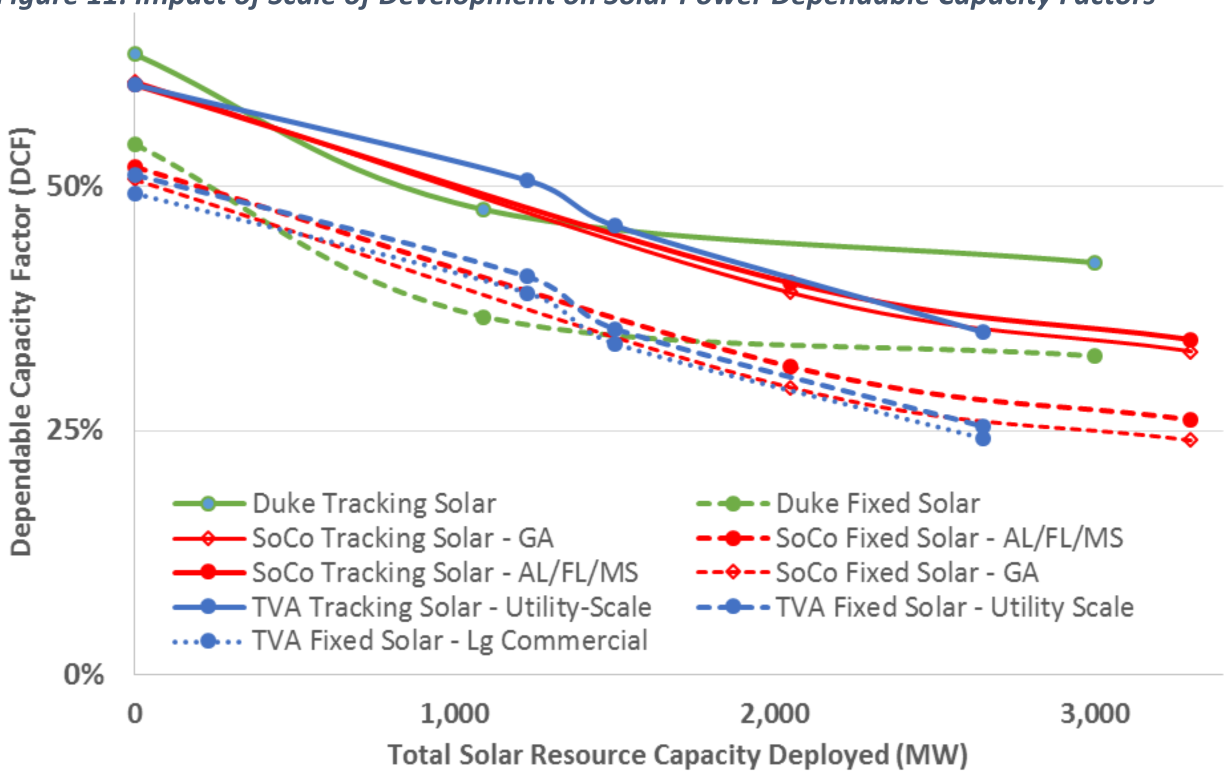
[23] Clean Line Energy's Plains & Eastern Line and Pattern Energy's Southern Cross HVDC projects reported separately. The differences are due to business model and losses imposed by intermediate AC transmission wheeling standards. The underlying wind data are identical.

A. Solar Power

Utility-scale solar power resources in the three utility service areas begin at very similar levels for both fixed mount systems (49-54% DCFs) and tracking systems (60-63%). However, as illustrated in Figure 11, at higher levels of deployment, the DCFs diverge somewhat.

The figure bears some explanation. Each point along the DCF curve represents the DCF that would be applied to the respective tranche, based on prior renewable energy development. For example, it is assumed that no renewable energy development occurs before Tranche 1 (the system load shape is assumed), so the total solar resource capacity deployed is 0 MW for purposes of calculating the Tranche 1 DCF. Then for Tranche 2, the amount of solar resource capacity deployed in Tranche 1 (see Section 6) is used to determine the seasonally modified net annual peaks for purposes of calculating the Tranche 2 DCF, as described in Step 4 (see Section 1).

Figure 11: Impact of Scale of Development on Solar Power Dependable Capacity Factors



One possible reason that the DCF curves diverge somewhat is that different amounts of wind are deployed (the curve is illustrated as a function of solar resource capacity deployment only to emphasize the primary correlation). For Duke Energy, which has the least wind power included in its scenario, the DCF values does not decrease as much as for the other two utilities. The overall finding for solar is that

[24] The first figure refers to utility-scale fixed mount solar systems, and the second figure refers to commercial-scale fixed mount solar systems. See note 16.

there is a consistent alignment of solar to system load shape across the Southeast, and the impact of solar development on DCF values decreases in a consistent manner.[25]

B. Regional Wind Power

Analysis of regional wind resources is less conclusive than for solar due to the limited data available for study. As discussed in Section 4-D, the TVA and Southern Company regional wind data are drawn from the same eight sites in the TVA service territory. (Even with identical data, differences in the DCF would be likely since the system load shapes differ.)

The main conclusion that can be drawn is that as renewable energy – mainly solar and HVDC wind imports in these scenarios – is developed, the DCF for regional wind increases, as illustrated in Figure 12. (Other relationships were examined, such as looking at wind resource capacity deployed, but the best relationship appeared to be with overall renewable energy deployment.) This occurs due to changes in the seasonally modified net annual peak, which is adjusted for renewable energy resource capacity installed during preceding tranches. As the seasonally modified net annual peak decreases, different hours now meet the 90% threshold requirement used to select the peak hours. Capacity factors for wind resources during these newly selected net peak hours are evidently significantly higher.

Figure 12: Impact of Scale of Development on Wind Power Dependable Capacity Factors[26]

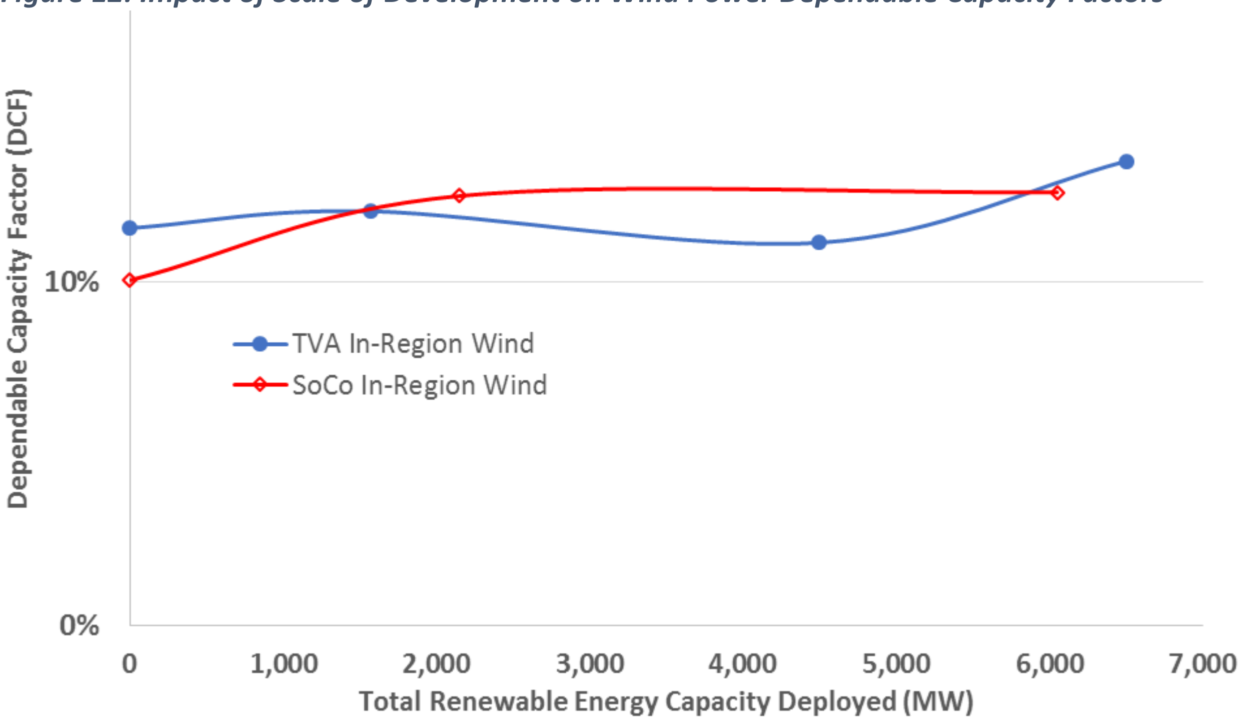


Figure 12 suggests that in-region wind DCFs increase slightly as renewable energy is deployed. However, as discussed in Section 4-D, regional wind data used in the TVA and Southern Company analyses were subsets of the same dataset from the TVA service territory. Beyond recognizing that the DCFs are similar

[25] Another impact of wind resources on solar DCFs is illustrated by the sharp, but small, drop in TVA's DCF values between Tranches 2 and 3 which is associated with by wind resource deployment in the TVA scenario.
[26] Duke Energy is not included in this figure because regional wind was not included in the development scenario for Duke Energy due to lack of available data.

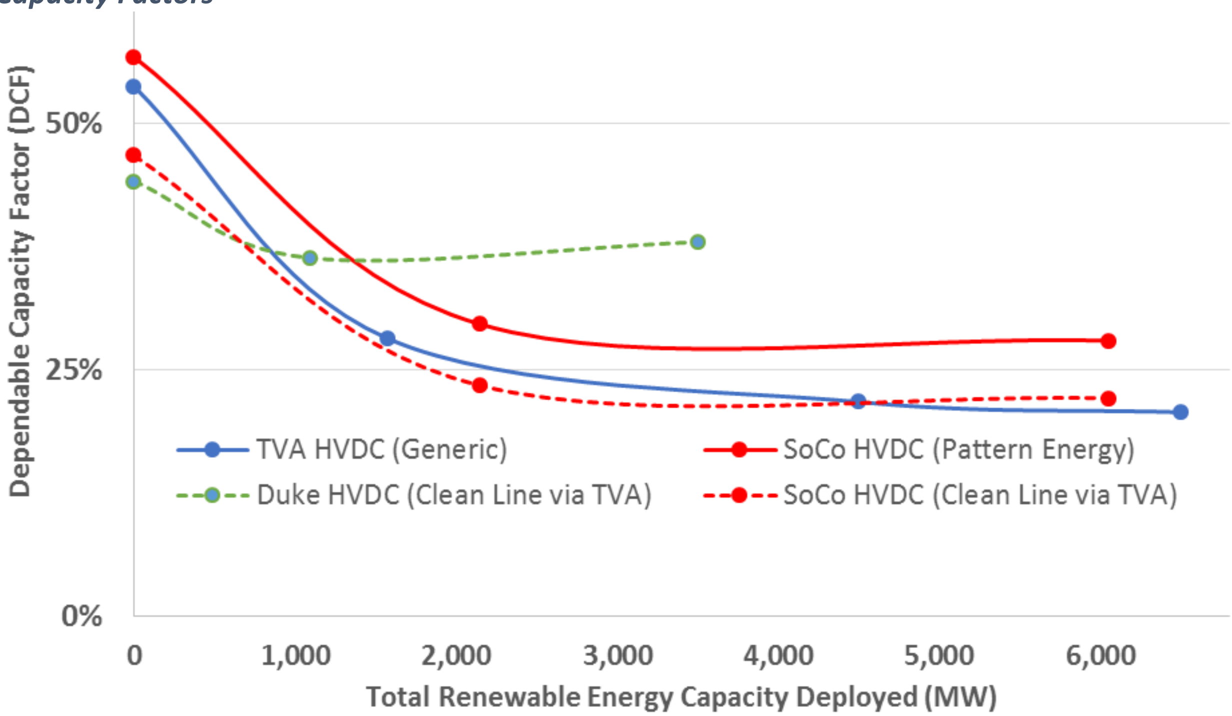
and may exhibit similar trends, the data used in this study are not adequate to reach definitive conclusions about dependable capacity factors for wind in the Southern Company service territory.

C. HVDC Imported Wind Power

In the case of HVDC imported wind power, two distinct features are illustrated (see Figure 13) that are not apparent for other resources. First, the initial introduction of primarily solar power in Tranche 1 (see Figure 9) can result in a significant decrease in the DCF for HVDC imported wind power, but as both wind and solar are added in subsequent tranches, the DCF for HVDC imported wind power remains relatively stable (most notably in contrast to solar power, see Figure 11). The second distinct feature is that this effect does not occur for Duke Energy, which could be explained by a significantly different system load shape.

In addition to those features, other differences in Figure 13 can be explained by the variation in the additional transmission losses applied to the Clean Line load shape when delivered to Southern Company and Duke Energy. Because the Clean Line project interconnects only to the TVA system, but the Pattern Energy project interconnects to both TVA and Southern Company, the Clean Line project's delivered energy and capacity are higher for the TVA system than for the more distant utility systems. As discussed in Section 4.E, the underlying wind data used to study both transmission projects are identical.

Figure 13: Impact on Scale of Development on HVDC Imported Wind Power Dependable Capacity Factors



D. Combined Analysis of Renewable Energy Resources

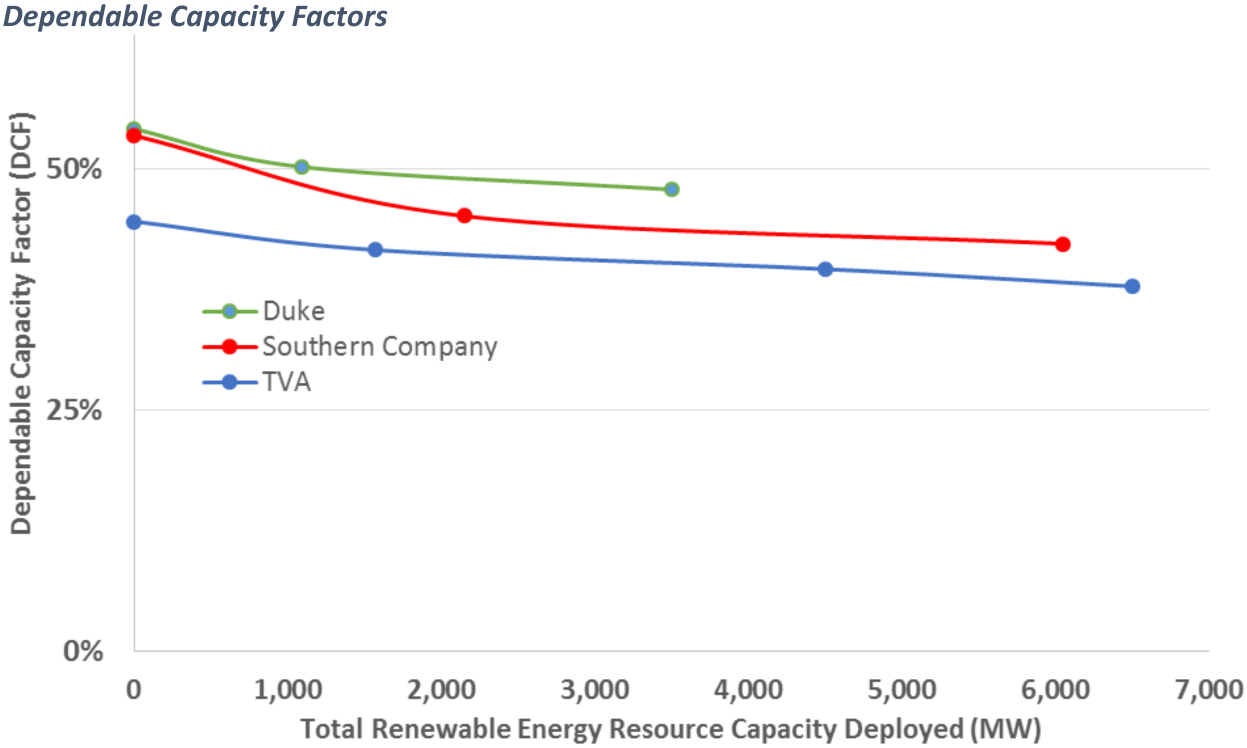
It is highly unlikely that any major utility will rely exclusively on a single renewable energy resource. As illustrated above, there can be significant interactions between the resources in terms of their dependable capacity value. For example, a utility that invests heavily in solar development for several years could find that the DCF for wind resources increases as the system peak hours are shifted into periods with relatively strong wind power production. The cliché that the whole is greater than the sum of the parts appears to apply.

One concern may be that the contribution of renewable energy resources to system dependable capacity may be highly sensitive to changes in the specific combination and deployment schedule of renewable energy resources. This does not appear to be the case, for two reasons.

First, as illustrated in Figure 14, even though there are significant differences between the utility scenarios (see Section 6), the resulting DCFs are not very different. It is clearly important to provide a reasonable forecast for the general ratio of resource technologies likely to be developed, but modest shifts in those ratios are not likely to substantially affect the total dependable capacity.

Second, the illustration also shows that as the resources are deployed, a renewable energy resources portfolio including a mix of strategies results in only a modest diminishing of the DCF as the resource mix is built out. In contrast, a utility that emphasizes a single resource could see a much steeper reduction in DCFs, as illustrated in Figure 11 and Figure 13. For planning purposes, a utility could select DCFs based on a reasonable forecast of the ratio of different technologies, conduct a capacity planning study, and then adjust the DCFs to correspond with the final plan.

Figure 14: Impact on Scale of Development on Blended Renewable Energy Resource Dependable Capacity Factors



Appendix B

Net Effective Reserve Margin Analysis: Impact of Generic Renewable Energy Resources on System Reliability

As discussed in Appendix A, utilities plan for a target reserve margin that is designed to minimize the overall cost of reliability to the customer. The System Peak Hours (SPH) method provides a measurement of an appropriate dependable capacity factor (DCF) forecast for variable energy resources for use in resource planning and other energy forecasting studies. While renewable energy resources generally perform very well during high demand periods, there may be high demand periods in which variable resources do not generate as much power as indicated by the DCF measurement. On the other hand, there will also be similar periods in which those resources generate more power than indicated by the DCF measurement.

Adding enough renewable energy to Southeastern utility systems to meet 10-20% of annual energy demand should trigger both of these counteracting effects on the level of risk that a utility has to manage. To balance these effects appropriately, a useful measurement of dependable capacity should be high enough to reflect how productive renewable energy will be during system peak hours and thus contribute to the system's capacity to serve load. Yet it should not be so high that it increases the risk that a centrally planned utility will have less capability to provide reliable service. In comparison to other averaging methods discussed briefly in Appendix A, the SPH method is designed to *avoid* misleadingly high or low results by arbitrarily excluding (or emphasizing) certain hours that are important (or unimportant) for a reliability measure.

For a utility system without significant variable renewable energy resources, the standard for determining the correct amount of system capacity is the target reserve margin. Most utilities maintain relatively up-to-date reserve margin studies, which consider the on-peak performance attributes for the existing mix of generation resources and characteristics of the utility systems' customer demand. At the target reserve margin, the loss of load probability (LOLP) is maintained at an economically optimal level.

By determining DCFs such that the target reserve margin is unaffected, the SPH method assumes a ceteris paribus approach, where the LOLP is unaffected by any changes to the characteristics of the generation mix or customer demand other than the introduction of renewable energy resources. This is similar to the Effective Load Carrying Capability (ELCC) method (described in Appendix A) which holds all other aspects of the system constant, while calculating the difference in loads that can be reliably served by a generation system "with" and "without" a defined level of renewable energy resources.[1]

In order to quantitatively demonstrate how effectively the SPH method balances the reliability effects of variable resources, a Net Effective Reserve Margin (NERM) is calculated to illustrate the effect of renewable energy on system reserves. Like the ratio method highlighted in Figure 5, the NERM technique is intended to act as a quantitative test to illustrate whether a proposed DCF is balanced and the capacity is "right."

[1] MISO, *Planning Year 2014-2015 Wind Capacity Credit* (December 2013).

As discussed in the main report, even if the number of hours with higher reliability risks is very low, it would be reasonable to be concerned that there could be specific hours in which a system that depends on high levels of renewable energy might be at greater reliability risk due to highly unusual circumstances. By considering aggressive, but realistic scenarios of renewable energy development in the context of actual system conditions for over a decade, the likelihood that an extreme event has been overlooked has been minimized. The NERM technique provides a finer resolution measurement of the changes in risks that the utility should plan to manage.

1. Relationship Between a Target Reserve Margin and a Dependable Capacity Factor

As discussed in Appendix A, utilities plan for a target reserve margin that is designed to minimize the overall cost of reliability to the customer. The target reserve margin is an optimal value: insufficient reserves put customers at risk of either system failures or expensive short-term market purchases, but excessive reserves guarantees that customers will pay for capacity that may not be sufficiently utilized to justify the cost. Most target reserve margins are set at a level that the utility believes will demonstrate achievement of an industry accepted reliability standard of 1 day in 10 years expected loss of load (LOLE).

The more difficult methods to measure DCFs use a loss of load probability (LOLP) calculation to apply the utility's reliability standard. While not explicitly relying on LOLP data, the SPH method is designed to track the LOLP concept closely by assuming a ceteris paribus approach, where the LOLP is unaffected by any changes to the characteristics of the generation mix or customer demand that occur other than the introduction of renewable energy resources. This is similar to the ELCC method, which holds all other aspects of the system constant, while calculating the difference in loads that can be reliably served by a generation system "with" and "without" a defined level of renewable energy resources.[2]

To implement the ELCC method or generate LOLP data, the utility must utilize robust distributions of load, weather, and unity performance uncertainty, including all production cost variables and unit constraints.[3] For example, MISO's most recent wind capacity report determined the "capacity credit at 176 individual wind [Commercial Pricing Nodes]," using a model that incorporates "historic operation performance data for all conventional unit types in the MISO system."[4] As with a robust reserve margin study, such a comprehensive study represents a significant resource commitment by a utility towards effective planning and would not likely be conducted frequently. Exploring a large number of alternative scenarios in an ELCC study effectively requires streamlined simulation practices.[5]

The key to the usefulness of the ELCC method is its ability to isolate the reliability effects for the resource in question from those of other resources. But utilities routinely plan for future development of generation resources without requiring a new reserve margin study (or an ELCC study) because utility integrated resource plans are conceptual guides to future investment choices. Detailed reserve margin

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[2] MISO, *Planning Year 2014-2015 Wind Capacity Credit* (December 2013).
[3] Carden, K, *Modeling Resource Adequacy Impacts of Integrating Intermittent Resources*, Astrape Consulting (February 2013).
[4] MISO, *Planning Year 2014-2015 Wind Capacity Credit* (December 2013), p. 4, 7.
[5] Pfeifenberger, JP et al, *Resource Adequacy Requirements: Reliability and Economic Implications*, prepared for the Federal Energy Regulatory Commission by The Brattle Group and Astrape Consulting (September 2013), p. 18.

or ELCC studies typically do not need to be updated frequently unless there are substantial system changes or other financial considerations such as capacity market auctions.

Ultimately, the purpose of establishing a valid DCF for variable resources is to ensure that resource plans developed using such factors are unlikely to affect the utility's reliability to such a degree that the results of a reserve margin study would change significantly. By measuring the DCF as the average capacity factor during peak hours, and by ensuring that those peak hours are the peak hours which would occur if a resource was deployed at substantial scale, the SPH method should closely track measurements made with LOLP data such as the ELCC method.

2. Net Effective Reserve Margin (NERM) Technique

Utilities typically establish target reserve margins such that "the cost of additional reserves plus the cost of reliability events to the customers [are] minimized."[6] It follows, therefore, that increasing or decreasing the reserve margin would result in higher costs to the customer.

To illustrate the effect of imposing these higher costs on the customer, Figure 1 contrasts the effective reserves during each hour of a thirteen-year period for the Tennessee Valley Authority (TVA). In this illustration, the effective reserves are defined as follows:

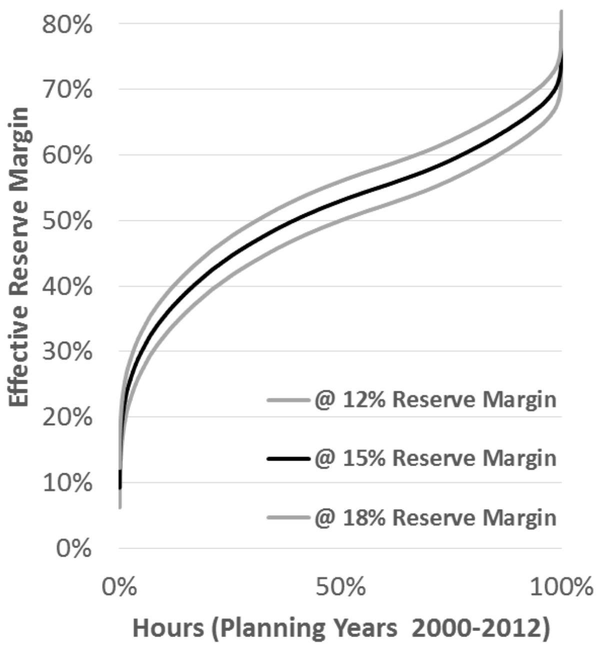
- RM = Reserve Margin
- Effective reserves (Hour n) = (1 + RM) x Forecast Annual Peak – Load (Hour n)
- RM_E = Effective reserve margin (Hour n) = Effective reserves (Hour n) / Forecast Annual Peak

This effective reserve margin curve can be viewed as the inverse of a load duration curve, with the multi-year dataset normalized to the forecasted annual peak.

The illustration also shows two hypothetical alternatives to TVA's 15% reserve margin: one in which TVA reduced its reserves to only 12%, and another in which it increased its reserves to 18%. It follows from the definition of the target reserve margin that if TVA used either a 12% or an 18% reserve margin, costs to the customer would *not* be minimized.

[6] TVA 2011 IRP

Figure 1: Effective Reserve Margin for Tennessee Valley Authority for 12%, 15% and 18% Target Reserve Margins



The NERM technique relies on this deduction to identify that any resource change which results in the effective reserve margin departing from the ideal 15% curve as having the potential to increase costs to the customer. Departures *above* the 15% curve reduce the LOLP for those hours, but also increase carrying costs for unnecessary capacity, and may be offset by lower costs in other respects (e.g., reduced fuel costs). Departures *below* the 15% curve increase the LOLP, and represent the costs of potential reliability events to the customer. (To quantify the net effect, it would be necessary to apply utility cost data and its system LOLP, but then an ELCC measurement would be practical and preferred.) If the net effect on the LOLP is an increase, the costs of potential reliability events to the customer could be offset through reliability-enhancing investments. This analysis does not study such investments but rather seeks to illustrate whether such a concern is even worth considering.

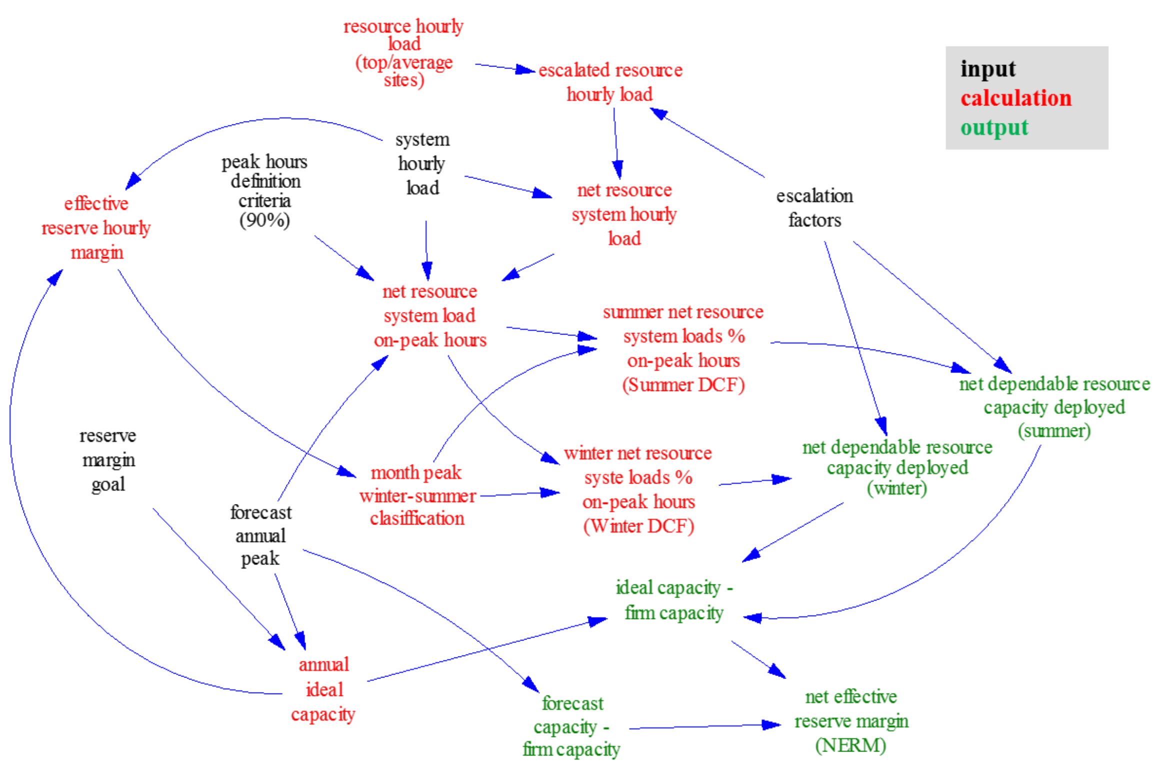
The effective reserve margin considers the utility system in its base configuration, a configuration that should be reasonably similar to the utility system studied to establish the target reserve margin. In order to study a utility system modified to include a substantial amount of variable resource deployment, the *net* effective reserve margin is calculated. In other words, the NERM technique is a way to estimate the impact of non-dispatchable energy resources on the dispatchable reserves required to maintain reliability. The assumption is that the LOLP curve for the net load is the same as the LOLP curve for the base system load, which seems reasonable as the system serving the net load is likely to be very similar to the base system.

The net effective reserve margin calculation is a modified version of the effective reserve margin, and is illustrated in casual loop diagram form in Figure 2. The NERM curve is associated with a specific scenario of renewable energy deployment with a nameplate capacity (NC) and a net dependable capacity (NDC) (calculated using the SPH method) for summer and winter.[7] The hourly capacity factor (CF) is obtained from the resource data files described in Appendix A.

- $NDC_S = DCF_S \times NC$
- Net effective reserves (Hour n) = ((1 + RM) x Forecast Annual Peak - NDC_S) - (Load(Hour n) - NC x CF(Hour n))
- Net RM_E = Net effective reserves (Hour n) / (Forecast Annual Peak - NDC_S)
- For winter, substitute $NDC_W = DCF_W \times NC$

The resulting NERM curves for specific resource deployment scenarios are presented for TVA, Duke and Southern Company in the following sections. First, the results of the most aggressive level of renewable energy scenarios tested for this project are reviewed. Next, individual resource studies are presented utilizing hypothetical 4 gigawatt (GW) development levels for individual technologies. It is unlikely that any of these utilities would invest in 4 GW of a single variable resource technology. Because the blended resource development scenarios demonstrate that DCFs are affected by the degree to which all variable resources are developed, it would be unreasonable to rely on these individual resource studies for planning purposes. However, it is interesting to compare the various resources and note differences in the impact of each resource on net effective reserve margins.

Figure 2: Net Effective Reserve Margin (NERM) Technique Calculations

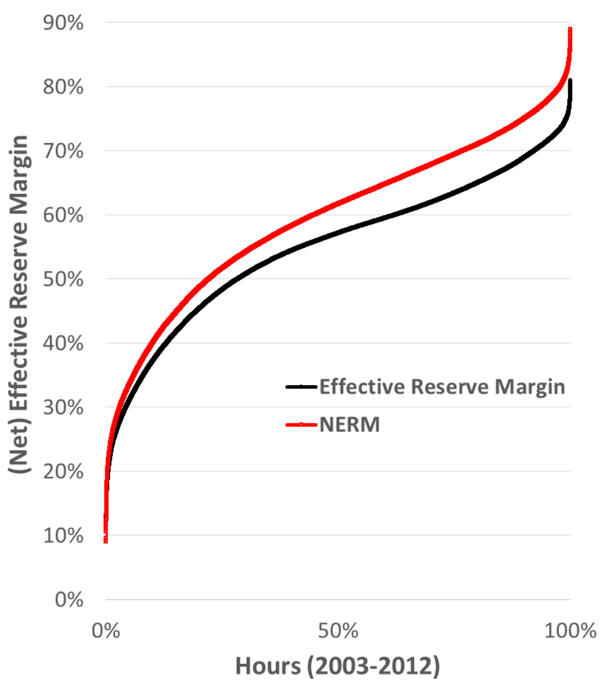


[7] The planning year is defined as beginning June 1. Winter months are November through March.

3. SPH Method Validation Using Aggressive Renewable Energy Development Scenarios

The overall impact of substantial renewable energy resources on the effective reserve margins of the utilities studied in this analysis is to increase hourly reserve levels during the vast majority of operating hours. For example, renewable energy with a nameplate capacity of 7.3 GW on the Southern Company system would reduce dispatchable generation requirements by about 3.1 GW. The 7.3 GW deployment represents roughly 20% of forecast annual peak loads for the Southern Company system, and is rated at an average DCF of 42.5%. Even with dispatchable capacity requirements reduced by roughly 10%, Figure 3 illustrates how effective hourly reserves (dispatchable generation plus hourly renewable energy generation) generally exceed the effective reserve margin. This effect is by design, the SPH method is designed to identify the level of generation that can be relied upon, but of course hourly generation often exceeds the dependable capacity.

Figure 3: Net Effective Reserve Margin for Southern Company, 7.3 GW Renewable Energy Scenario



Similar NERM curves can be produced for individual resource development scenarios, and for all utilities studied in this analysis. Any impression that well planned renewable energy deployments will lead to frequent shortfalls in available resources is simply unsupported by available data.

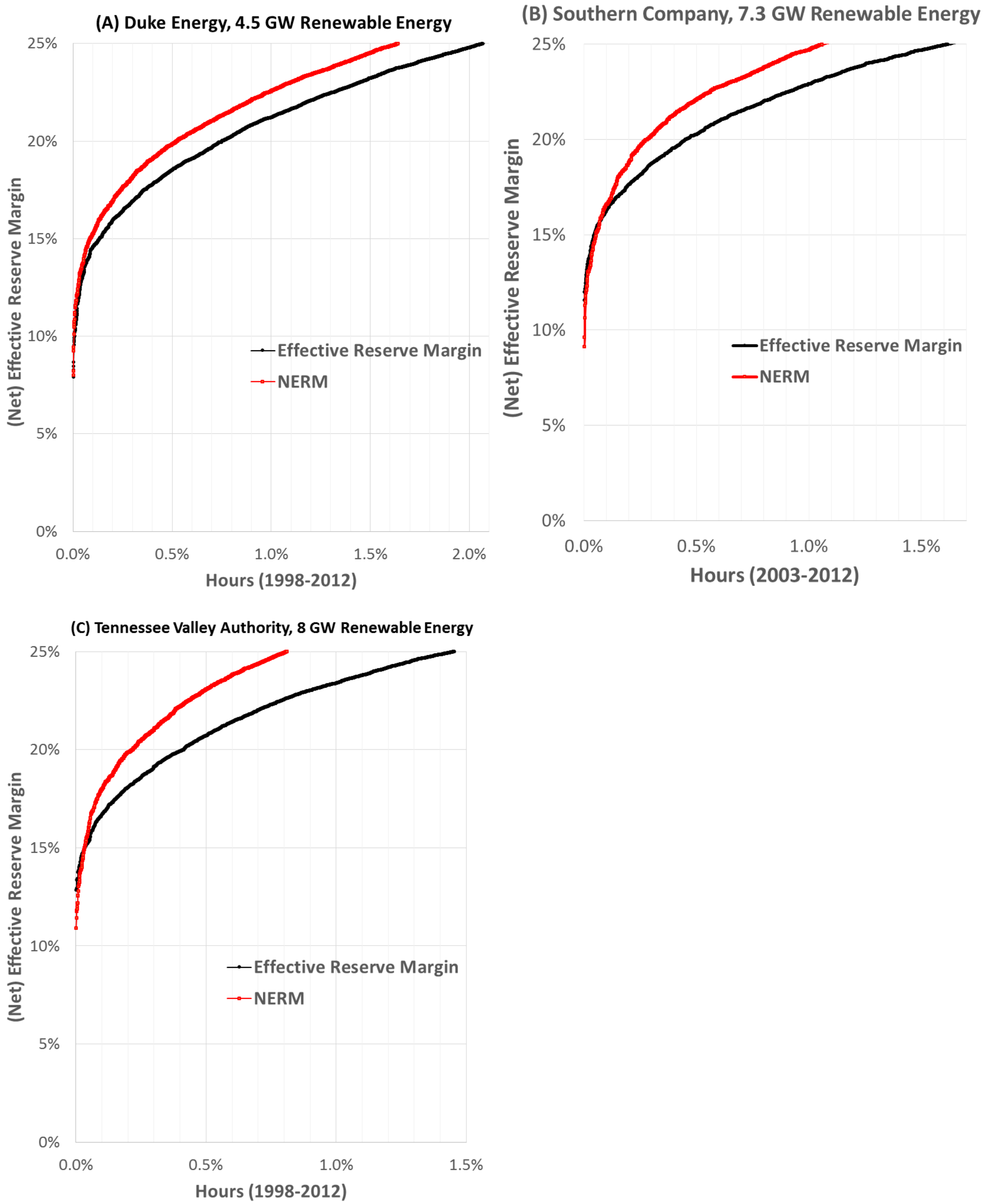
Of course, from a reliability perspective, the focus is not on the vast majority of hours in which the system has more than ample available resources, but on those few hours in which the system is potentially challenged to meet customer demand. As illustrated in Figure 4, the NERM curve follows the effective reserve margin curve closely even during the most challenging 0.1% of hours.

- For Duke Energy (North and South Carolina), there were no hours in 15 years with reduced reserve margin relative to the baseline.[8]
- For Southern Company, renewable energy deployment resulted in 6 hours in 10 years with reduced reserve margin relative to the base case. The increase was less than 1% for all but 2 of the 6 hours.
- For Tennessee Valley Authority, renewable energy deployment resulted in 11 hours in 15 years with reduced reserve margin relative to the base case. The increase was less than 1% for all but 4 of the 11 hours.

The NERM curve also exhibits the benefit of substantially fewer hours with a NERM of less than 25% relative to the base effective reserve margin. These effects are quantified and elaborated on below.

[8] The effective reserve margin curve for Duke Energy illustrates that the number of hours with an effective reserve margin for the base system is roughly 35% higher than for Southern Company or TVA. This may suggest that the reserve margins for Duke Energy carry more risk and less cost than those of Southern Company and TVA.

Figure 4: Net Effective Reserve Margin for (A) Duke Energy, (B) Southern Company and (C) Tennessee Valley Authority with Substantial Renewable Energy Development



The findings illustrated above suggest two ways in which the LOLP may be affected by substantial deployment of renewable energy resources. First, for a few hours captured in the dataset, the LOLP is evidently increased (an adverse effect). When the net effective reserve margin curve dips significantly below the effective reserve margin curve, the data indicate an increased likelihood of a reliability incident.

However, counteracting that effect is the large reduction in the number of hours with a low net effective reserve margin (a positive effect). It is not possible to quantitatively demonstrate which effect is larger.[9] It is statistically more probable, of course, that the event would occur during an hour with a lower effective reserve margin because quite obviously the utility system has less tolerance for generator outages at that level. So when dealing with an increase in probabilities on the one hand, and a decrease in the number of hours with significant probabilities on the other, a quantitative solution can only be calculated in an ELCC study framework. Nonetheless, it is possible to arrive at some quantitative observations.

Two quantities are calculated to represent these competing effects.

- **Higher risk hours**: The number of hours that would need to be removed from the net effective reserve margin curve in order for that curve to be substantially identical to or in excess of the effective reserve margin curve.[10]
- **Reliability ensured hours**: The reduction in the number of hours with a significant probability of reliability incidents.[11]

As illustrated in Figure 5, the ratio of higher risk hours to reliability ensured hours is 1:76 or less, with a clearly positive impact appearing to occur on the Duke Energy system on which no higher risk hours result from setting capacity values based on the SPH method.

Figure 5: Impact of Substantial Renewable Energy Development Scenarios on Reliability

	Higher Risk Hours	Reliability Ensured Hours	Ratio
Duke Energy (North and South Carolina)	0.0 % (0)	0.734 % (558)	0:100
Southern Company	0.007 % (6)	0.549 % (481)	1:80
Tennessee Valley Authority	0.008 % (11)	0.639 % (840)	1:76

Thus, NERM technique illustrates that the SPH method can support planning outcomes that do not adversely affect the level of reserves on utility systems on a daily or hourly basis. Some hours are more reliable, some hours are less reliable. Concentrating on lower reliability in some particular hour would ignore the improvements in many other hours. In other words, the SPH method is an effective tool for

[9] The underlying methods of a target reserve margin study involve stochastic evaluation of probabilities. For example, in a random draw of circumstances, the utility may not experience a reliability event during an hour with an effective reserve margin of 10%, but might experience a reliability event during an hour with an effective reserve margin of 20%.

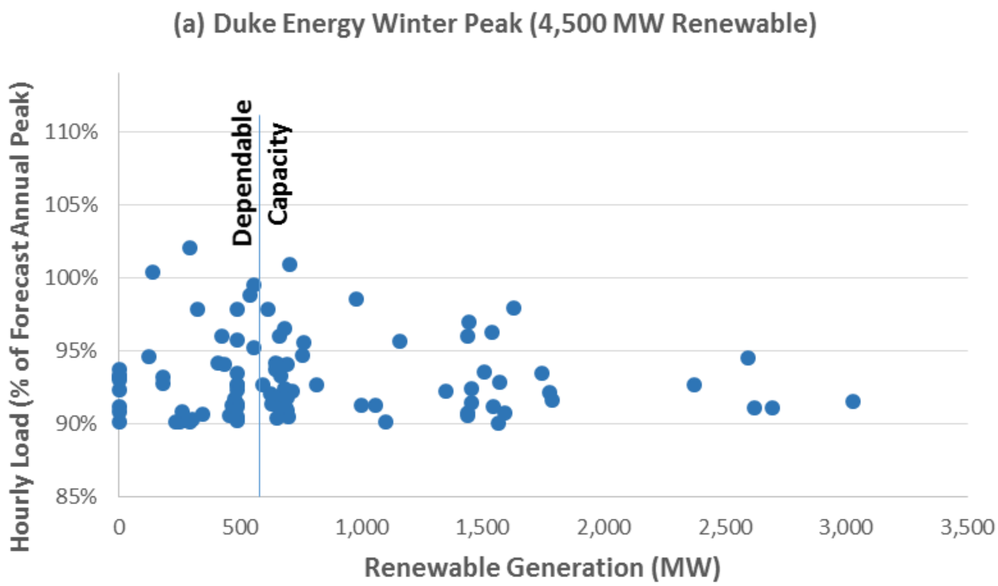
[10] In other words, the number of hours in which the utility might consider taking additional measures to ensure no added risk of a reliability incident.

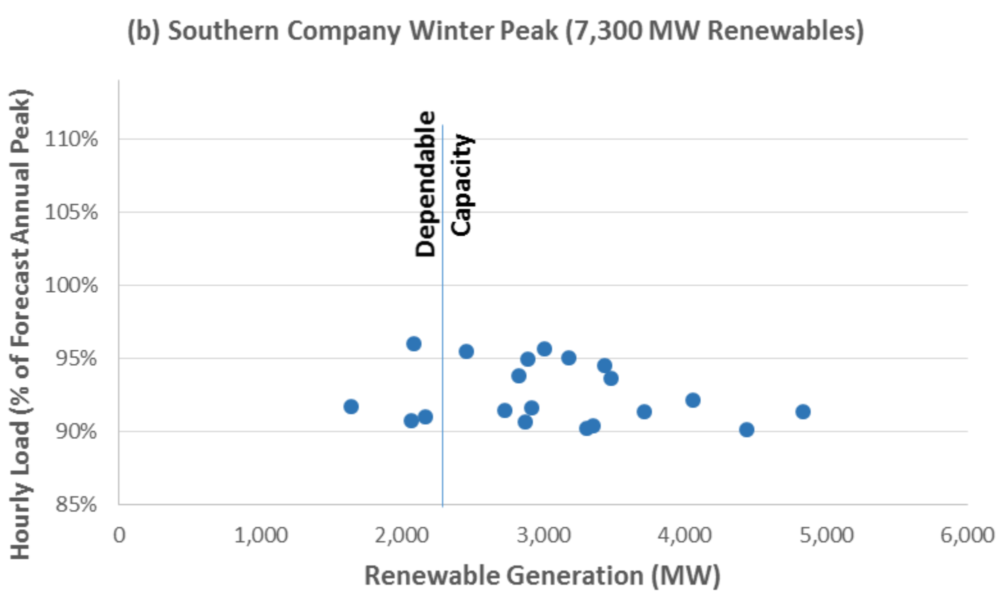
[11] For this project, the number of hours was compared up to the 25% (net) effective reserve margin level, consistent with the SHP method use of a 90% below forecast annual peak plus a 15% target reserve margin.

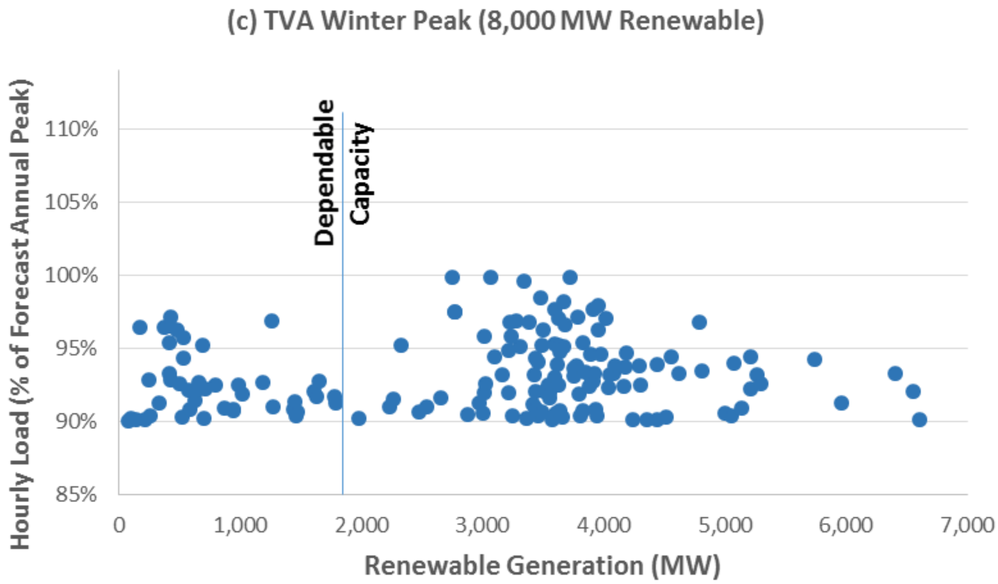
ensuring that renewable energy can be studied in a resource planning model without compromising reliability.

These reliability effects were also examined for winter peaking concerns, as discussed in Section 4 of the report. In Figure 6, the three utilities are analyzed by estimating renewable generation output during hours in which winter loads exceed 95% of the annual peak forecast by the utility for the corresponding planning year.

Figure 6: Renewable Generation During Winter Peak Hours for (A) Duke Energy, (B) Southern Company and (C) Tennessee Valley Authority







4. Individual Resource Studies of SPH Method Using 4 GW Development Levels

Although several utilities have published estimates for DCFs (or equivalent terms) at current system levels, none has yet published a projected value based on substantial development of renewable energy. As illustrated in Figure 4 of the main report, studies by a number of utilities have demonstrated that the dependable capacity for variable resources decreases with significant increases in resource deployment. Evidently, the relationship varies by resource, utility and planning assumptions (such as deployment of other renewable energy resources).

It is unlikely that any Southeastern utility would invest in 4 GW of a single variable resource technology. Even if solar is emphasized by some utilities, a variety of technologies and interconnection types would occur. Each combination of technology and interconnection type can result in a different DCF value. As the blended resource development scenarios demonstrate, DCFs are affected by the degree to which all variable resources are developed. For these reasons, it would be unreasonable to rely on these individual resource studies for planning purposes.

Nonetheless, it is interesting to compare the various resources and note differences in the impact of each resource on net effective reserve margins. In combination with the findings related to blended resource scenarios, utility planners can use individual resource studies to inform their planning decisions. Accordingly, hypothetical 4 gigawatt (GW) development levels for individual technologies are provided for review. As illustrated in Figure 7,[12] using the SPH method to calculate DCFs for individual resources does not result in an obvious increase in risk of resource inadequacy, even at 4 GW of nameplate resource deployment.

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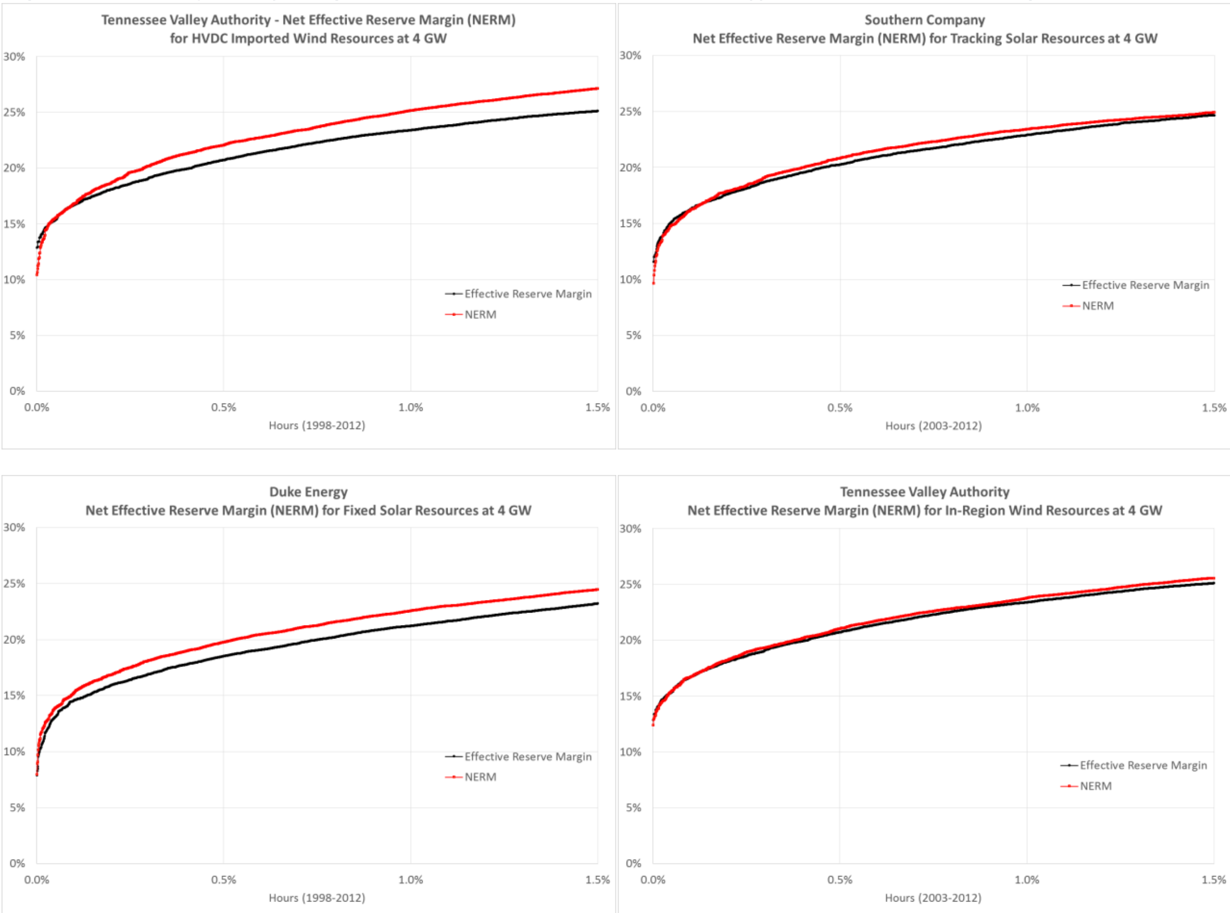
[12] One example is provided for each of the four technologies studied. Graphs for other utilities studied look similar for each resource.

Figure 7: Examples of Single Resource Scenarios on Net Effective Reserve Margin



Appendix C

Impact of Renewable Energy on the Ramping of Conventional Generation Plants in the Southeast

To maintain reliability, utilities must continuously match the demand for electricity with supply on a second-by-second basis. Much of this is automated, but utilities must plan for and actively control power plant units to increase or decrease generation in response to changes in demand. As renewables are deployed on the grid, a portion of the utility's supply capacity is represented by variable generation resources with more limited (or nonexistent) control capabilities.

Net load curves are used to illustrate the utility's challenge to direct controllable resources to match both variable demand and variable supply. A net load is calculated by subtracting the forecasted electricity production from variable generation resources, wind and solar, from the forecasted load.

One specific concern is that utilities will face challenges of supplying large amounts of power within a short time period to replace the electricity lost by solar power as the sun sets. A more general concern is that utilities will find it more costly or risky to meet operating challenges associated with variable renewable energy resources. As discussed in the main paper, a substantial problem of this nature is unlikely to appear in the Southeast.

Two analyses were conducted to reach this finding. In the first analysis (see Section 1), two historical episodes were selected from each utility dataset to illustrate extreme operating conditions. One episode was selected to represent a system peaking event, identifying a multi-day period with peaks in excess of the utility's forecast annual peak.[1] The second episode was selected to represent a low load event with high renewable energy generation, identifying a period in which renewable energy is at its highest share of total electric generation.

In the second analysis (see Section 2), the entire data set was examined statistically for individual renewable resources (e.g., in-region wind), as well as a scenario of combined renewable resources. Ramp rates were calculated over 1-hour increments.[2] This provided a broad view, considering hours in which renewable energy improved system ramp rates as well as those in which ramp rates became more challenging.

1. Case Studies on Episodes of Extreme Operating Conditions

Case studies of extreme operating conditions are often used to demonstrate the impact of variable renewable energy on utility systems. The two most extreme conditions would be system peaking events and low load events (associated with high renewables penetration).

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[1] Each of the six case study episodes span almost the full range of potential renewable energy generation. The Southern Company and TVA scenarios include substantial amounts of both solar and wind resources; average renewable generation capacity factors are about 40% in system peaking events and 50% in low load events. Because the Duke Energy analysis includes mostly solar resources, the average renewable generation capacity factors in the system peaking event and the low load event are lower, about 35%.

[2] Three hour ramp rates were also calculated for a portion of the analysis, but the results were not sufficiently different from the one hour ramp rate studies to suggest any benefit to more extensive study.

One example of each episode was selected for each utility. Coincidentally, for all three utilities, the August 7-10, 2007 episode was selected as a highly challenging peaking event. For the low load event with high renewable energy generation, the most challenging episodes for each utility occurred in April, but on different dates in 2011 and 2012. Net load curves are provided for each episode, at varying levels of renewable energy (including both wind and solar resources in each scenario, as described in Appendix A.)

For each episode, data are summarized (see Figure 1 and Figure 2) for each of the utilities in the following categories.

- System peak – the highest demand on the (net) load curve for the episode
- Swing – the total ramp up from minimum (net) load to maximum (net) load; all values are provided on the net load curve graphs, with the minimum and maximum values summarized in the figures below
- Ramp – the average ramp rate over the ramping period (e.g., swing divided by hours)

These system level case studies do not consider market power imports or exports, nor do they include consideration of localized issues that might require dispatch or transmission contingency planning. Figures 3, 4, 5, 6, 7 and 8, illustrate the load impacts that varying levels of renewable generation would have on each utility under a summer peaking event versus springtime low-load event.

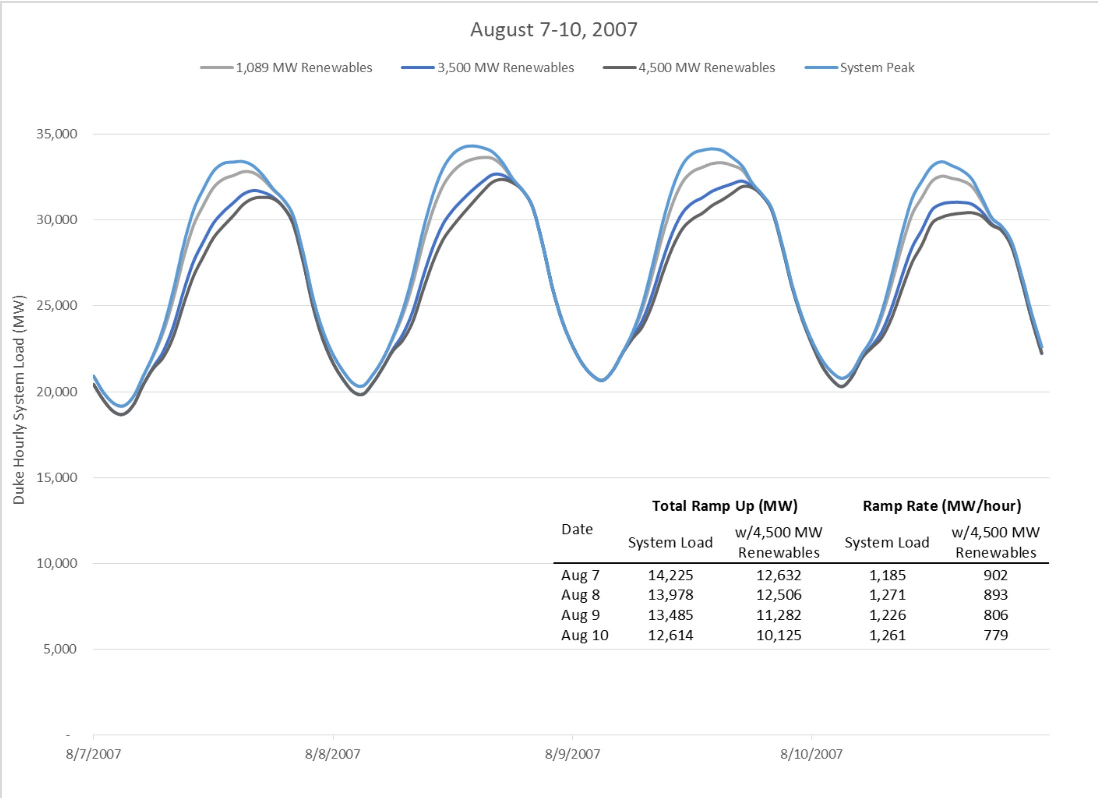
Figure 1: System Peaking Event Case Studies

	System Peak (MW)	**Minimum Swing** (MW)	**Maximum Swing** (MW)	**Maximum Ramp** (MW/hr)
Duke Energy (North and South Carolina)	34,323	12,614	14,225	1,271
Southern Company	36,029	13,100	13,674	1,140
Tennessee Valley Authority	33,315	11,681	12,912	1,076
High Renewable Generation Scenario				
Duke Energy (North and South Carolina)	32,223	10,125	12,632	902
Southern Company	34,217	11,242	14,447	1,032
Tennessee Valley Authority	31,034	11,335	14,180	1,013

Figure 2: Springtime Low Load / High Renewables Event Case Studies

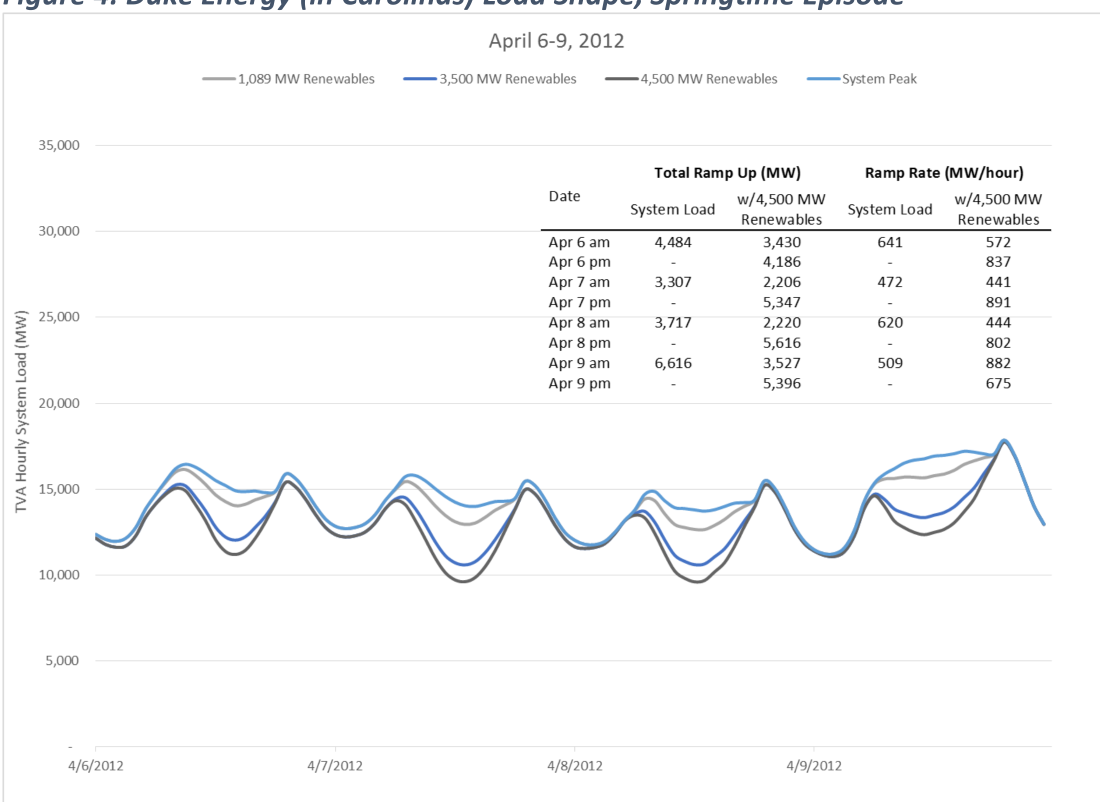
	System Peak (MW)	**Minimum Swing** (MW)	**Maximum Swing** (MW)	**Maximum Ramp** (MW/hr)
Duke Energy (North and South Carolina)	17,857	3,307	6,616	641
Southern Company	21,062	3,405	7,702	804
Tennessee Valley Authority	17,975	4,230	6,446	645
High Renewable Generation Scenario				
Duke Energy (North and South Carolina)	17,857	2,220	5,616	891
Southern Company	18,458	4,897	7,671	979
Tennessee Valley Authority	14,432	3,229	7,395	975

Figure 3: Duke Energy (in Carolinas) Load Shape, Summer Peak Episode



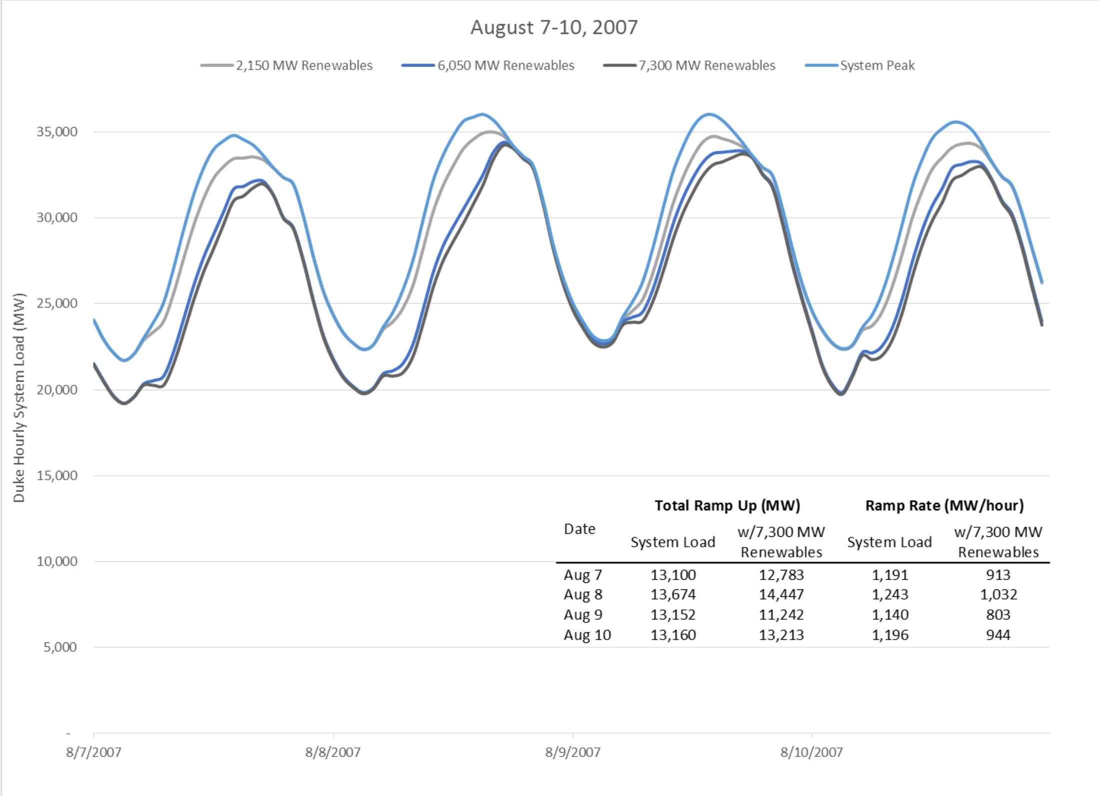
Date	Total Ramp Up (MW)		Ramp Rate (MW/hour)	
	System Load	w/4,500 MW Renewables	System Load	w/4,500 MW Renewables
Aug 7	14,225	12,632	1,185	902
Aug 8	13,978	12,506	1,271	893
Aug 9	13,485	11,282	1,226	806
Aug 10	12,614	10,125	1,261	779

Figure 4: Duke Energy (in Carolinas) Load Shape, Springtime Episode



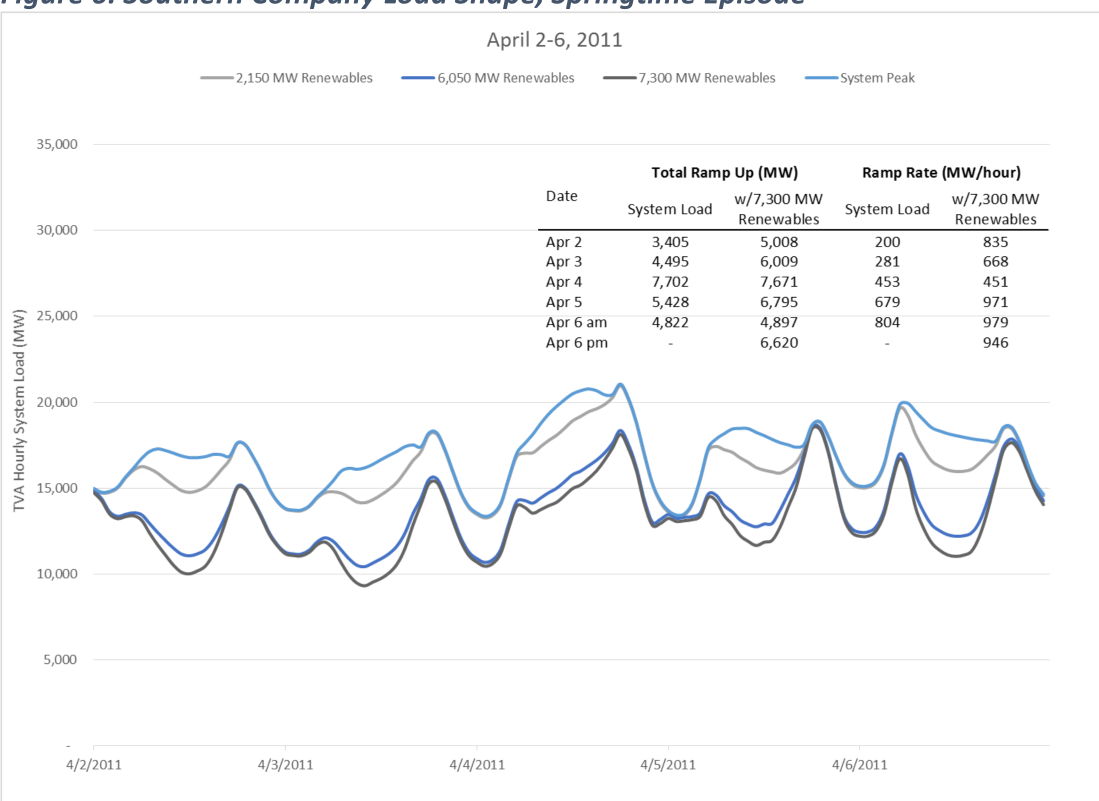
Date	Total Ramp Up (MW)		Ramp Rate (MW/hour)	
	System Load	w/4,500 MW Renewables	System Load	w/4,500 MW Renewables
Apr 6 am	4,484	3,430	641	572
Apr 6 pm	-	4,186	-	837
Apr 7 am	3,307	2,206	472	441
Apr 7 pm	-	5,347	-	891
Apr 8 am	3,717	2,220	620	444
Apr 8 pm	-	5,616	-	802
Apr 9 am	6,616	3,527	509	882
Apr 9 pm	-	5,396	-	675

Figure 5: Southern Company Load Shape, Summer Peak Episode



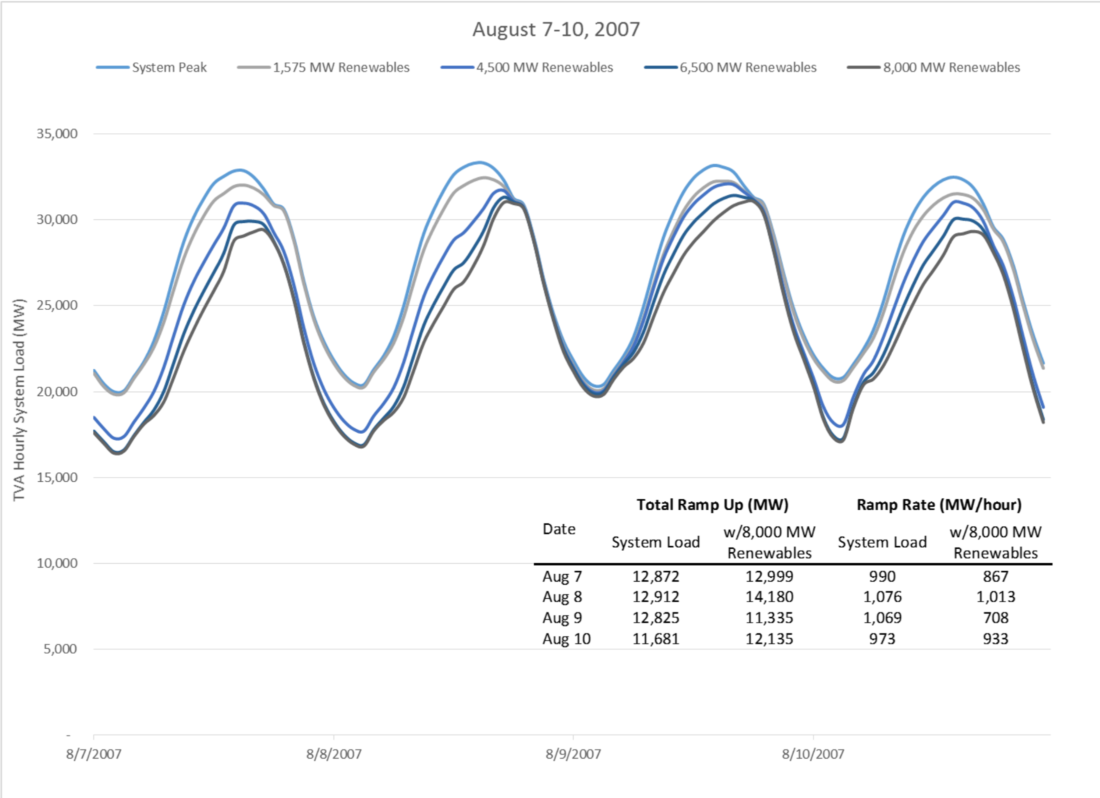
Date	Total Ramp Up (MW)		Ramp Rate (MW/hour)	
	System Load	w/7,300 MW Renewables	System Load	w/7,300 MW Renewables
Aug 7	13,100	12,783	1,191	913
Aug 8	13,674	14,447	1,243	1,032
Aug 9	13,152	11,242	1,140	803
Aug 10	13,160	13,213	1,196	944

Figure 6: Southern Company Load Shape, Springtime Episode



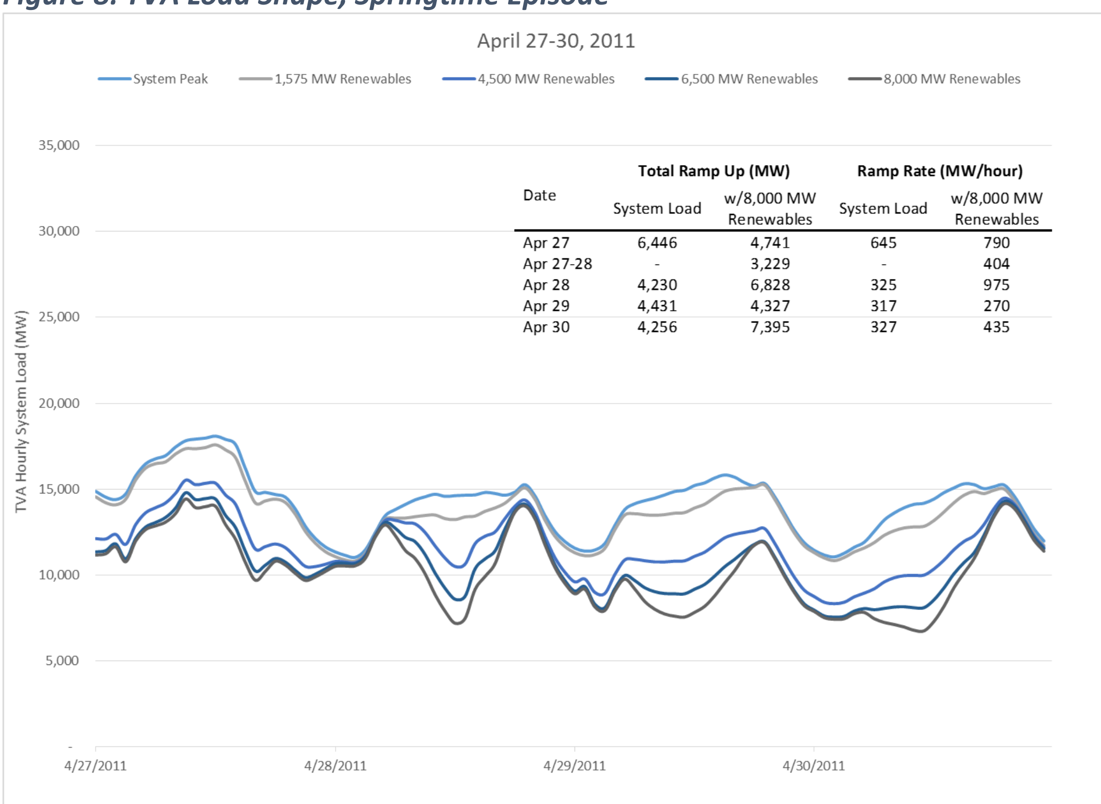
Date	Total Ramp Up (MW)		Ramp Rate (MW/hour)	
	System Load	w/7,300 MW Renewables	System Load	w/7,300 MW Renewables
Apr 2	3,405	5,008	200	835
Apr 3	4,495	6,009	281	668
Apr 4	7,702	7,671	453	451
Apr 5	5,428	6,795	679	971
Apr 6 am	4,822	4,897	804	979
Apr 6 pm	-	6,620	-	946

Figure 7: TVA Load Shape, Summer Peak Episode



Date	Total Ramp Up (MW)		Ramp Rate (MW/hour)	
	System Load	w/8,000 MW Renewables	System Load	w/8,000 MW Renewables
Aug 7	12,872	12,999	990	867
Aug 8	12,912	14,180	1,076	1,013
Aug 9	12,825	11,335	1,069	708
Aug 10	11,681	12,135	973	933

Figure 8: TVA Load Shape, Springtime Episode



Date	Total Ramp Up (MW)		Ramp Rate (MW/hour)	
	System Load	w/8,000 MW Renewables	System Load	w/8,000 MW Renewables
Apr 27	6,446	4,741	645	790
Apr 27-28	-	3,229	-	404
Apr 28	4,230	6,828	325	975
Apr 29	4,431	4,327	317	270
Apr 30	4,256	7,395	327	435

2. Statistical Analysis of Ramp Rates

To place these case studies in context, the entire data set was examined statistically for individual resources as well as the combined resource scenarios. Ramp rates were calculated over 1-hour increments.[3] This provided a broad view, considering hours in which renewable energy improved system ramp rates as well as those in which ramp rates became more challenging. The vast majority of utility ramp rates, <u>with or without</u> up to the maximum 8 GW of renewable energy analyzed here, remain below 5% of total system capacity. The main result of adding renewable energy into a ramp rate analysis is that some hours have increased ramps, and other hours have decreased ramps.

Because the utilities have similar peak loads and ramp rates, it was practical to apply the same simple analytic method to each utility. As discussed in Appendix A, due to limitations on available data, the data sets were different in size.

- Duke Energy (in the Carolinas): 1998-2012, including 131,496 hourly records
- Southern Company: 2003-2012, including 87,672 hourly records
- Tennessee Valley Authority: 1998-2012, including 131,496 hourly records

It should be noted that each of these utility systems is a dispatching authority, although each distributes power through affiliated utilities.

Hourly ramp rates were calculated and sorted into seven bins for each utility. Hourly ramp rates with an increase or decrease in (net) load of less than 1,000 MW were considered "low ramp rates."[4] For each utility the low ramp rate represented 81-86% of the hourly ramp rates under reported historic system loads. Higher ramp (up or down) rates were grouped in increments of +/- 1,000 MW as illustrated on the graphs.

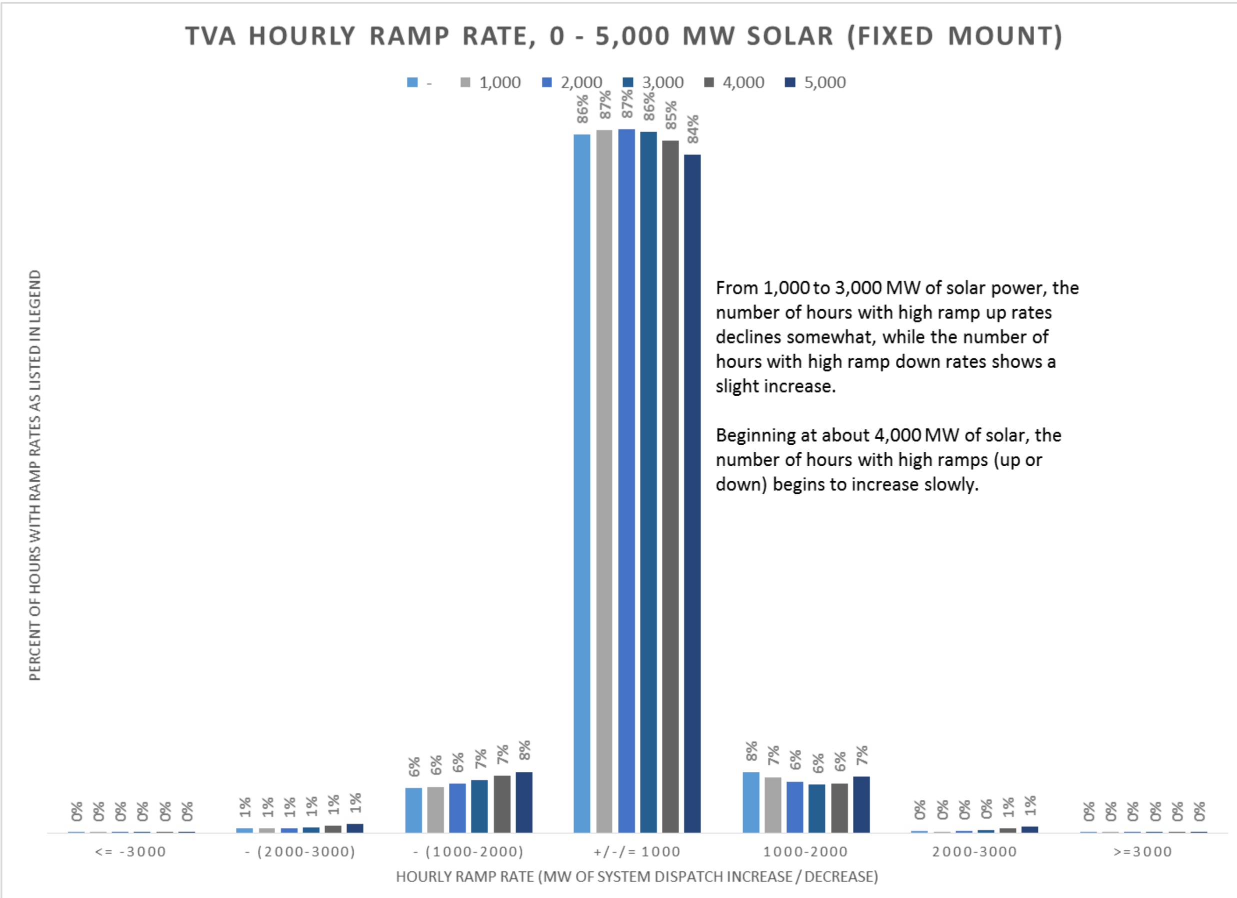
For comparison with the system load baseline, net loads were calculated at increasing levels of renewable energy development. For individual resources, net loads were calculated for 1-5 GW of nameplate capacity. The study of ramp rates for individual resources included a total of twelve datasets (3, 4 and 5 distinct resource technologies for the utilities). A complete set of net load graphs was not completed after it became clear that the findings were repetitive. Furthermore, it should be re-emphasized that it is not likely that a utility would develop several gigawatts of capacity from a single renewable energy technology, leaving the others undeveloped.

For solar power, all analyses showed that for the first several gigawatts of solar power development, the number of hours with high ramp up rates declines somewhat, while the number of hours with high ramp down rates shows a slight increase. Overall, for solar power, up to about 4 GW of development can be supported with operating ramps being *either slightly improved or about the same* as the system without solar. Beyond 4 GW, ramp rates on the system slowly increase in overall challenge but there is no point at which dramatic changes in system ramp rates occur. This trend is illustrated in Figure 9, which

[3] Three-hour ramp rates were also calculated for a portion of the analysis, but the results were not sufficiently different from the one-hour ramp rate studies to suggest any benefit to more extensive study.
[4] This "low ramp rate" value was selected arbitrarily and is not based on any particular system operation standard.

considers fixed mount solar systems over an hourly interval. Similar findings occurred for solar tracking systems, for three-hour ramp rates, and for other utilities.

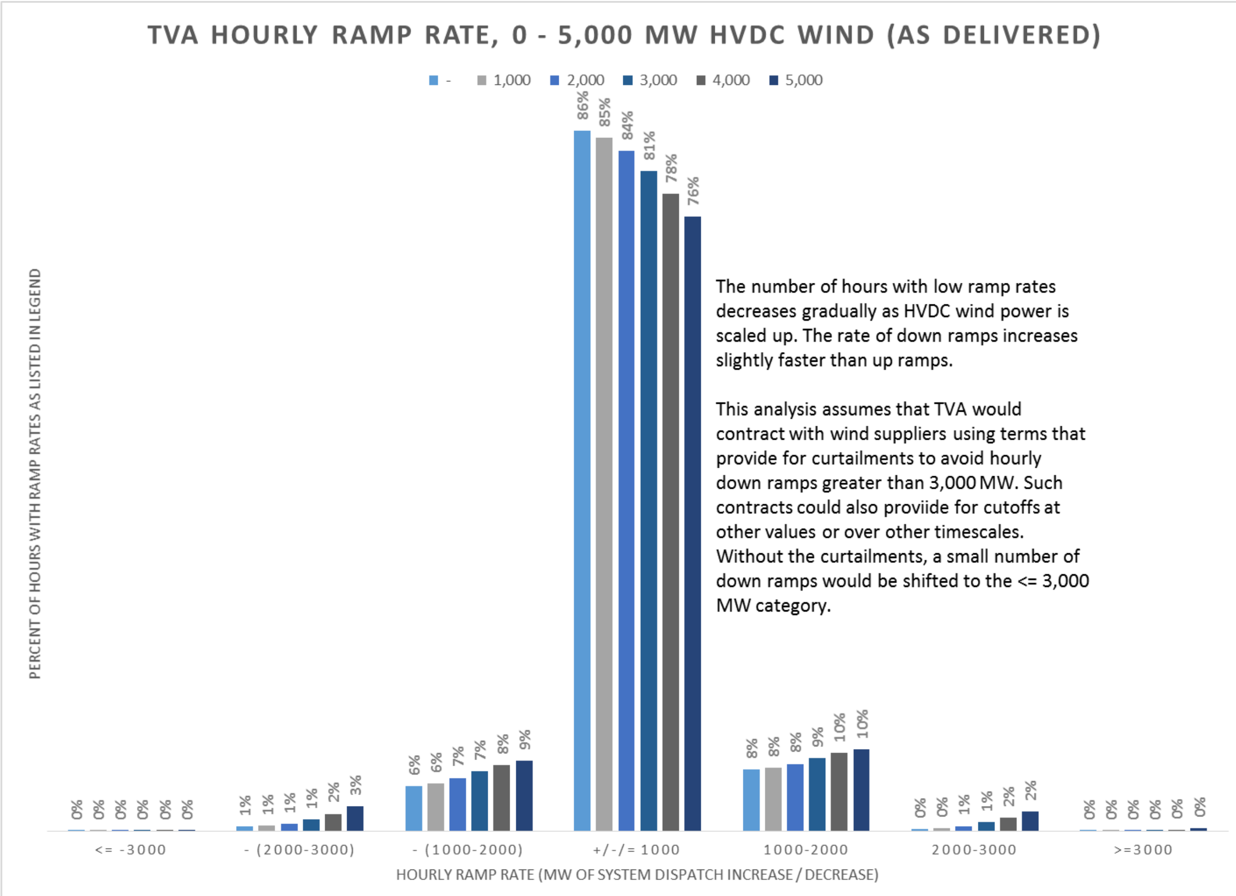
Figure 9: TVA Hourly Ramp Rate, 0 – 5 GW Solar Fixed Mount Systems



Wind energy presents a more significant operational challenge in terms of ramp rates. However, at the levels of wind power that are likely to be deployed on utility systems, the impacts of wind power on ramp rates appears to be modest. For example, due to the size of projects under development and utility standards regarding primary reserves and resource availability, TVA is unlikely to add more than 5 GW of wind power to its system from all sources (whether regional, interconnected via existing AC transmission, or imported via new HVDC transmission projects) over the next decade. Other Southeastern utility systems are more constrained in terms of access to wind resources over the next decade.

As illustrated in Figure 10, even 5 GW of wind power modeled on the basis of HVDC wind resources would have a relatively modest impact on the TVA system. The main impact appears to be in terms of ramping the system down at a greater frequency. Fortunately, this impact can be mitigated by introducing contract terms that provide the utility with the opportunity to curtail wind generation to allow for other resources to be ramped down more gradually (after a brief curtailment, the wind generation would be restored to full output). Similar, but somewhat less significant effects occurred for regional wind resources; regional wind resources are unlikely to be developed at the same scale as HVDC wind imports in any event, so the system impacts on ramping would be of less consequence.

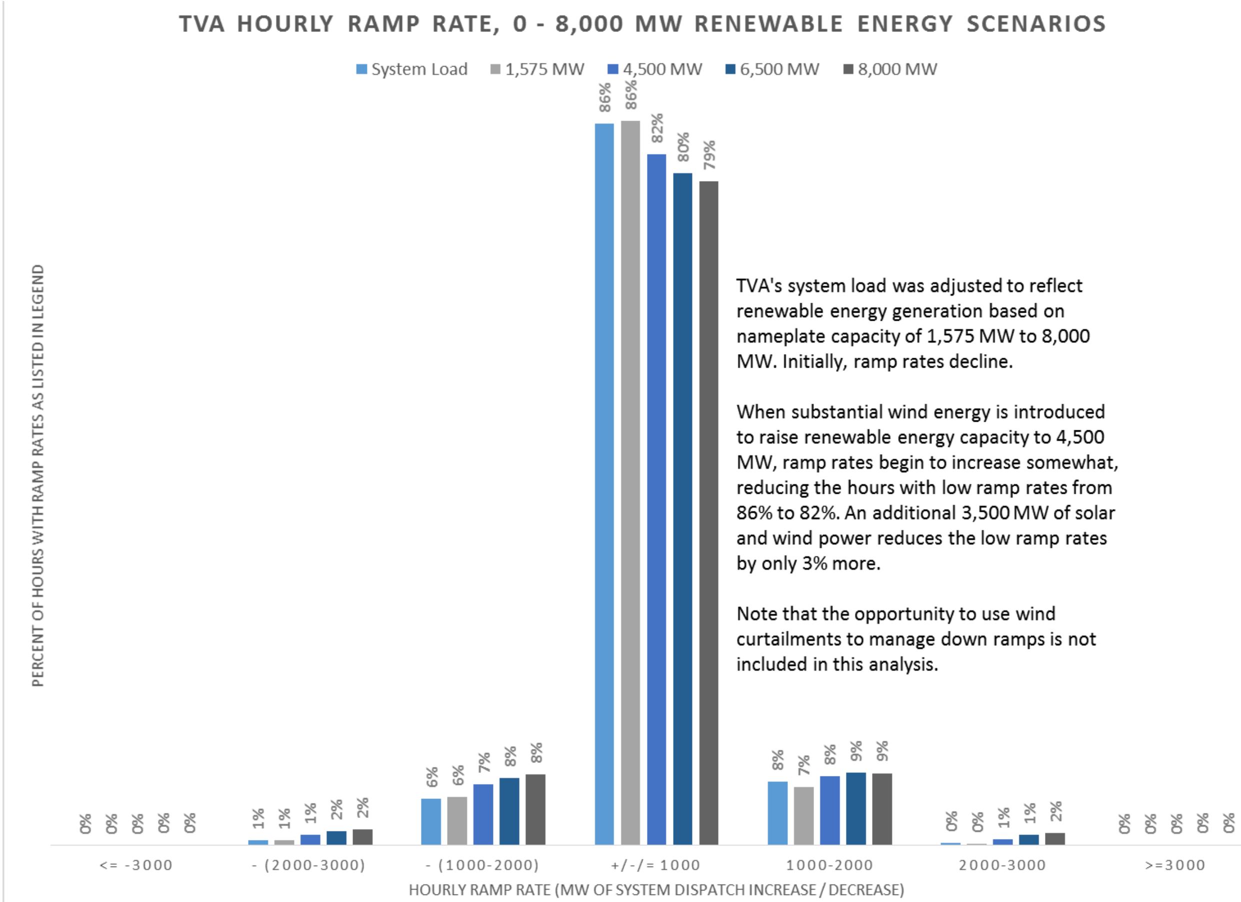
Figure 10: TVA Hourly Ramp Rate, 0 – 5 GW HVDC Wind Imports



In scenarios reflecting various blends of renewable energy resource technologies, the method was altered slightly. While retaining an identical baseline of no renewable energy, the incremental amounts of renewable energy corresponded to the renewable energy development scenarios described in Appendix A, Section 4. The resulting analyses of the three utility scenarios are presented in Figure 11, Figure 12, and Figure 13.

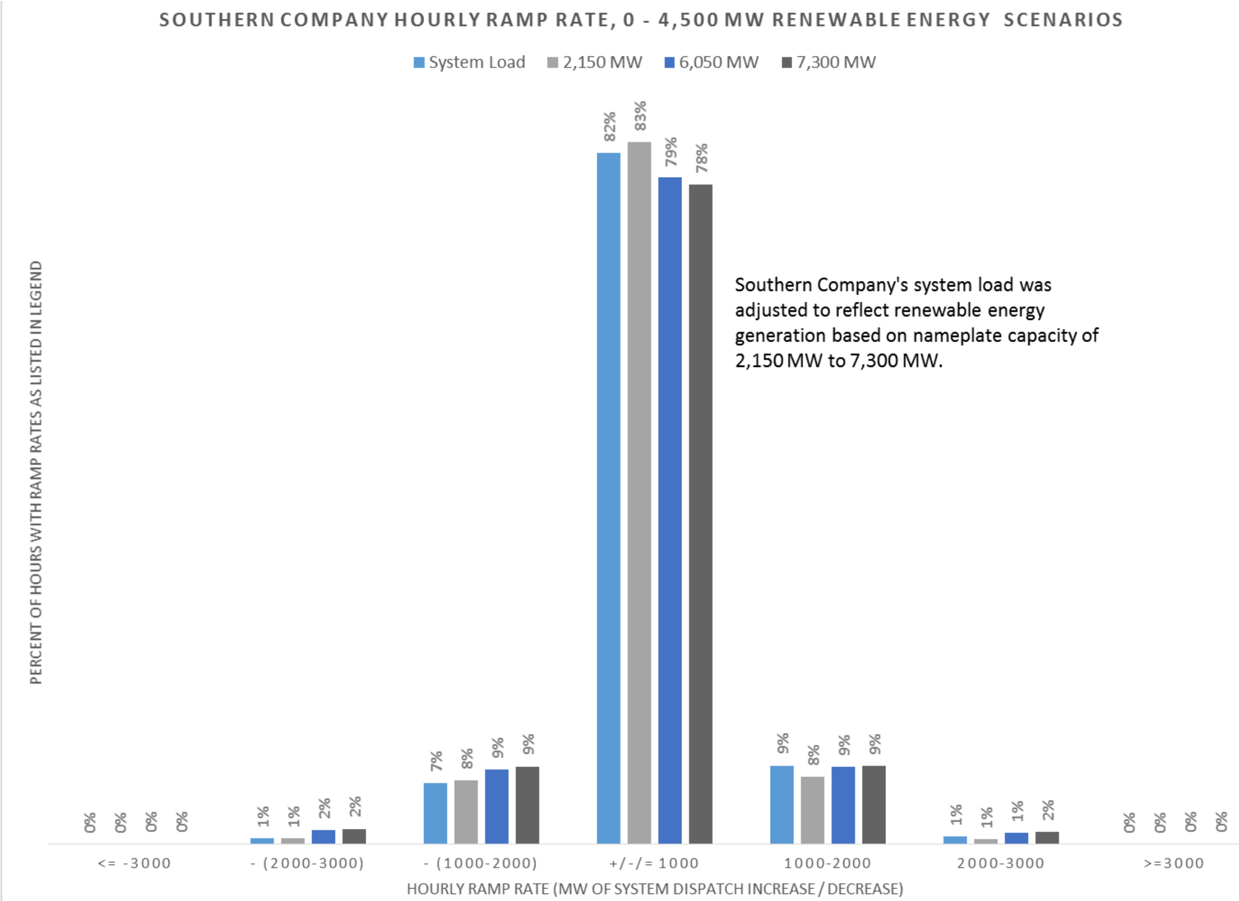
These analyses suggest that wind has more impact than solar on the magnitude of changes to ramp rates. For example, TVA Tranche 2 (4,500 MW in Figure 11) results in a reduction in low ramp rates from 86% of hours to 82% of hours. The composition of Tranche 2 is dominated by 3,000 MW of wind, mostly HVDC imports (see Appendix A, Section 4). This correlates closely with the ramp rate impacts of HVDC wind, a reduction to 81%, for 3,000 MW of HVDC wind imports (see Figure 10). The close relationship between the HVDC-only ramp rates and the combined renewable energy scenario contrasts with other findings in this analysis. For combined resource scenarios, the DCFs for solar and wind tended to combine in a synergistic manner at higher levels of resource development. With respect to ramp rates, there appears to be relatively little synergy.

Figure 11: TVA Hourly Ramp Rate, 0 – 8 GW Renewable Energy Scenario



The results for Southern Company, as illustrated in Figure 12, are similar to those for TVA. The main impact on ramp rate frequencies relates to the introduction of HVDC wind resources, but the impacts are relatively modest.

Figure 12: Southern Company Hourly Ramp Rate, 0 – 7.3 GW Renewable Energy Scenarios



For Duke Energy, as illustrated in Figure 13, ramp rate frequencies are not affected very much since the project did not have access to wind data for resources available to the Duke Energy region. The performance of the Duke Energy scenario is similar to solar (see Figure 9 for example) because of the emphasis on solar energy resources.

Figure 13: Duke Energy Hourly Ramp Rate, 0 – 7.3 GW Renewable Energy Scenarios